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Examining the Economic Impact of Human Recognition for Women Farmers in Malawi

Ebelechukwu Obioma Dometilla Maduekwe

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Malawi 1: Excerpt from field research with women farmers in Nsanje and Lilongwe districts, Malawi

Abstract

Objective: Women's access to resources like land are influences by norms, inter, and intra personal interactions prevalent in the society. Rights to resources like land for agriculture in sub-Saharan Africa are linked to several factors, embedded in negative institutional structures in the society. These negative structures are harmful to women and often deprive them of human recognition, dignity and property rights within their communities. They also influence women's bargaining power with significant impact on individual and household wellbeing. Several researches have linked women's power dynamics to unfavorable institutional structures, yet, researchers rarely consider the nexus where multidimensional poverty reduction, land ownership and access, and the missing components of human development like human recognition intersect. In agrarian countries like Malawi, gendered institutions influence women farmers' land ownership and access, however, national policies fail to address, substantially, the intersection of poverty, the perception of women as economic agents and as humans with equal rights i.e., their human recognition, with overall economic development. This work is one of the first empirical analysis that examines an intangible concept of human development - human recognition, and outlines its impact on the wellbeing, including land access, for women farmers.

Methodology: To this end, this research examines the indicators of multidimensional negative human recognition within the domains of interaction for women namely: self, household, community/institution using secondary data from the Demographic and Health surveys. Using the Alkire and Foster method of multidimensional poverty counting, it derives the human recognition deprivation index (HRDI), the headcount ratio (H), the deprivation intensity (A), and established a dichotomous censored count of deprived women (c). Second, using logistic regression analysis, it identifies human recognition deprived women and analyze social-demographic and socioeconomic factors influencing human recognition deprivation in Malawi and Peru. Examining women farmers on the household level, it outlines principal-agent

bargaining model and uses ordinary least squares plus instrumental variable regressions (OLS & IV) to demonstrate the power dynamics underpinning the prevalence of non-cooperative resource bargaining for women farmers in agrarian households in Malawi. It also outlines the detrimental effects such a bargaining structure has on overall wellbeing. Third, it is important for policy makers and researchers to rigorously establish evidence or lack of human development components like negative human recognition, found in secondary data with primary field data. To that effect, the research also proposes and applies a multilevel sampling approach to development survey data using geographical information systems (GIS) for random spatial sampling; and personal digital assistants (PDAs) with global positioning system (GPS) for the household systematic random sampling. Finally, using structural equation modelling (SEM), it analyzes the impact of positive human recognition on land use choice and community discourse from a cross-section of women farmers in central and southern Malawi in the primary survey.

Findings: The Alkire-Foster method allows negative human recognition within and across domains of interaction to be identified. Using a range of robust properties including decomposing by domains and sub-groups, its finds women in Malawi as multidimensionally human recognition deprived with deprivation that varies across decomposed domains and sub-groups. In identifying human recognition deprived women, it observes that education, overall, reduces the likelihood of negative human recognition for women. It also observes additional heterogeneous outcomes for women farmers and land ownership for agriculture. Under the non-cooperative bargaining model of principal-agent frame work, this research finds that significant non-monotonous trade-offs between farm land access and women farmers' negative human recognition exists These trade-offs have significant detrimental effect on household wellbeing. The applied multilevel sampling approach used for the field data collection in Malawi shows that relevant data can be collected from field surveys with lower sampling costs, lower sampling bias with rapid aggregation quality data after the survey. Finally, evidence from the primary survey data shows that women farmers with positive human recognition, living in communities with better institutional recognition make improved/responsible land use choices and have better participation in community discourse, with significant implications on land management outcomes.

Recommendations: For policy makers, accounting for missing dimensions of human development and its effects on land access matters. Policy investigators are recommended to use different domain cut-offs and weights to identify crucial target populations for interventions. Overall, women's human recognition can be improved with good social policies and education. Power dynamics rooted in institutional structures is one of the pillars of negative human recognition provision, thus, re-engineering gendered institutions all spheres of social interactions, can improve women's bargaining power for resources such as land and overall wellbeing. Using a multilevel sampling approach with GIS, GPS; and PDAs can support researchers and policy investigators that wish to examine dimensions of human development, land management for population research and generate relevant survey data, under budget constraints. Finally, policies for improving land use choices and implement responsible land management, should include reforms that can reconcile the gap between land owners and land managers as well as reduce barriers to women's community participation as a pathway to overall sustainable development.

Zusammenfassung

Ziel: Der Zugang von Frauen zu Ressourcen wie Land wird durch Normen, Inter- und intrapersönliche Interaktionen beeinflusst, die in der Gesellschaft vorherrschen. Die Rechte auf Ressourcen wie Land für die Landwirtschaft in Subsahara-Afrika sind mit mehreren Faktoren verbunden, die in negative institutionelle Strukturen in der Gesellschaft eingebettet sind. Diese negativen Strukturen sind für Frauen schädlich und berauben sie oft der menschlichen Anerkennung, Würde und Eigentumsrechte in ihren Gemeinschaften. Sie beeinflussen auch die Verhandlungsposition von Frauen mit erheblichen Auswirkungen auf das Wohlbefinden von Individuen und Haushalten. Mehrere Forschungen haben die Machtdynamik von Frauen mit ungünstigen institutionellen Strukturen verknüpft, doch die Forscher betrachten selten den Zusammenhang zwischen multidimensionaler Armutsbekämpfung, Landbesitz und Zugang und den fehlenden Komponenten der menschlichen Entwicklung wie der menschlichen Anerkennung. In Agrarländern wie Malawi beeinflussen geschlechtsspezifische Institutionen den Landbesitz und den Zugang von Bäuerinnen, aber die nationalen Politiken befassen sich nicht wesentlich mit dem Schnittpunkt von Armut, der Wahrnehmung von Frauen als Wirtschaftsakteure und als Menschen mit gleichen Rechten, d.h. ihrer menschlichen Anerkennung, mit der allgemeinen wirtschaftlichen Entwicklung. Nach meinem besten Wissen ist dies die erste empirische Analyse, die ein immaterielles Konzept der menschlichen Entwicklung - die menschliche Anerkennung - untersucht und ihre Auswirkungen auf das Wohlbefinden, einschließlich des Zugangs zu Land, für Landwirtinnen umreißt.

Methodik: Zu diesem Zweck wird in dieser Dissertation zunächst untersucht, die Indikatoren für eine multidimensionale negative menschliche Anerkennung innerhalb der Bereiche der Interaktion für Frauen nämlich: Selbst, Haushalt, Gemeinschaft/Institution mit sekundären Daten aus der Demographie und Gesundheit Umfragen. Mit der Alkire and Foster-Methode der

multidimensionalen Zählung der Armut leitet sie den Human Recognition Deprivation Index (HRDI), den Personalbestand (H), die Deprivationsintensität (A) ab und etabliert eine dichotome zensierte Anzahl von benachteiligten Frauen (c). Zweitens, mit Hilfe der logistischen Regressionsanalyse, identifiziert es menschliche Anerkennung benachteiligte Frauen und analysiert sozial-demographische und sozioökonomische Faktoren, die den Verlust der menschlichen Anerkennung in Malawi und Peru beeinflussen. Bei der Untersuchung von Landwirtinnen auf Haushalt-Ebene skizziert sie das Modell der Verhandlungen zwischen Hauptakteuren und Vertretern und verwendet gewöhnliche kleinste Quadrate plus instrumentelle variable Regressionen (OLS & IV), um die Machtdynamik zu demonstrieren, die der Prävalenz von nicht-kooperativen Ressourcenverhandlungen für Landwirtinnen in landwirtschaftlichen Haushalten in Malawi zugrunde liegt. Es werden auch die nachteiligen Auswirkungen einer solchen Verhandlungsstruktur auf das allgemeine Wohlbefinden aufgezeigt. Drittens ist es für politische Entscheidungsträger und Forscher wichtig, rigoros Beweise oder das Fehlen von Komponenten der menschlichen Entwicklung wie negative menschliche Anerkennung, die in Sekundärdaten mit Primärfeld-Daten gefunden werden, zu ermitteln. Zu diesem Zweck schlug diese Dissertation auch vor und wandte einen mehrstufigen Sampling-Ansatz auf Entwicklungserhebungsdaten unter Verwendung von geografischen Informationssystemen (GIS) für zufällige räumliche Stichproben an; und persönliche digitale Assistenten (PDAs) mit Global Positioning System (GPS) für die systematische Stichprobenziehung im Haushalt. Schließlich, mit Hilfe von Strukturgleichungsmodellen (SEM), analysiert diese Dissertation die Auswirkungen einer positiven menschlichen Anerkennung auf die Wahl der Landnutzung und den Gemeinde-Diskurs aus einem Querschnitt von Landwirtinnen in Zentral- und Süd-Malawi, die aus der Primärerhebung abgeleitet wurden.

Ergebnisse: Diese Dissertation skizziert seine Ergebnisse wie folgt: Die Alkire-Foster-Methode ermöglichtes, negative menschliche Erkennung innerhalb und zwischen den Bereichen der

Interaktion zu identifizieren. Mit einer Reihe von robusten Eigenschaften einschließlich der Zerlegung durch Domänen und Untergruppen, diese Dissertation stellt fest, dass Frauen in Malawi sind mehrdimensional menschliche Anerkennung beraubt, die sich zwischen zerlegten Domänen und Untergruppen. Bei der Identifizierung der menschlichen Anerkennung benachteiligte Frauen mit der dichotomen Anzahl der benachteiligten Frauen, diese Dissertation findet Bildung, insgesamt reduziert die Wahrscheinlichkeit einer negativen menschlichen Anerkennung für Frauen. Darüber hinaus werden zusätzliche heterogene Ergebnisse für Landwirtinnen und Landbesitz für die Landwirtschaft beobachtet. Im Rahmen des nicht kooperativen Verhandlungsmodells der Principal-Agent-Rahmenarbeit zeigt diese Dissertation, dass signifikante nicht-monotone Kompromisse zwischen dem Zugang zu landwirtschaftlichen Flächen und der negativen menschlichen Anerkennung von Landwirtinnen bestehen Diese Kompromisse haben erhebliche nachteilige Auswirkungen auf das Wohlbefinden der Haushalte. Da es wichtig ist, Beweise für Komponenten der menschlichen Entwicklung wie negative menschliche Erkennung in den Primärfelddaten in Einklang zu bringen, führte der angewandte mehrstufige Stichprobenansatz in der Felddatensammlung in Malawi zu niedrigeren Stichprobenkosten, geringerer Sampling-Bias und schnellen Aggregationsqualitätsdaten nach der Studie. Schließlich zeigt diese Dissertation anhand von primären Erhebungsdaten, dass Landwirtinnen mit besserer positiver menschlicher Anerkennung, die in Gemeinschaften mit besserer institutioneller Anerkennung leben, verbesserte/verantwortliche Landnutzungsentscheidungen treffen und eine bessere Beteiligung am gesellschaftlichen Diskurs haben, was erhebliche Auswirkungen auf die Ergebnisse der Landbewirtschaftung hat.

Empfehlungen: Für politische Entscheidungsträger, unter Berücksichtigung fehlender Dimensionen der menschlichen Entwicklung und ihrer Auswirkungen auf den Zugang zu Land. Den Forschern wird empfohlen, unterschiedliche Domain Cut-offs und Gewichte zu verwenden, um wichtige Zielpopulationen für Interventionen zu identifizieren. Insgesamt argumentieren wir, dass die menschliche Anerkennung von Frauen durch eine verbesserte Sozialpolitik und Bildung verbessert werden kann. Da wir die Machtdynamik, die in institutionellen Strukturen verwurzelt ist, als eine der Säulen der negativen menschlichen Anerkennung identifiziert haben, wird die Neugestaltung geschlechtsspezifischer Institutionen in allen Bereichen der sozialen Interaktion die Verhandlungsmacht von Frauen für Ressourcen wie Land verbessern und das allgemeine Wohlbefinden verbessern. Die Verwendung eines mehrstufigen Stichprobenansatzes mit GIS, GPS und PDAs unterstützt Forscher und politische Ermittler, die Dimensionen der menschlichen Entwicklung, Landmanagement für die Bevölkerungsforschung und die Generierung relevanter Erhebungsdaten unter Budgetbedingungen untersuchen wollen. Schließlich sollten Maßnahmen zur Verbesserung der Landnutzungsentscheidungen und zur Umsetzung einer verantwortungsvollen Landbewirtschaftung Reformen beinhalten, die die Kluft zwischen Landbesitzern und Landmanagern ausgleichen und Hindernisse für die Beteiligung von Frauen an der Gemeinde als Weg zur allgemeinen Entwicklung abbauen können.

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Abbreviations

ADF	African Development Fund
AVE	Averaged Variance Extracted
CFI	Comparative Fit Index
CTS	Conflict Tactics Scale
DHS	Demographic and Health Survey
DEFF & DEFT	Design Effects
FAO	Food and Agriculture Organization
GIS	Geographical Information Systems
GPS	Global Positioning System
HH	Household
HDD	Household Dietary Diversity
HIV	Human Immune Virus
HRD	Human Recognition Deprivation
HRDI	human recognition deprivation index
IV	Instrumental Variable
LUB	Land Use Behaviour
LV	Latent Variables
LIML	Limited Information Maximum Likelihood
MEGS	Malawi Economic Growth Strategy
ML	Maximum Likelihood Estimation
MEFF & MEFT	Misspecification-Effects
MPRS	Malawi Poverty Reduction Strategy
MPI	Multidimensional Poverty Index
NSO	National Statistics Office

OLS	Ordinary Least Squares
PEI Africa	Poverty-Environment Initiative - Africa
PDA	Personal Digital Assistants
PPES	Population Proportional to Estimated Size
PSU	Primary Sampling Unit
RGC	Random Geographic Cluster
RAND	Random Number Function
RMSEA	Root Mean Squared Error of Approximation
STATA	Software for Statistics and Data Science
SD	Standard deviation
SE	Standard Error
SRMR	Standardized Root Mean Square Residual
SEM	Structural Equation Modelling
TA	Traditional Authorities
2SLS	Two Stage Least Square
UN Women	United Nations Women
UNDP-UNEP	United Nations Development Programme - United Nations Environment Programme
US$	United States Dollars
USAID	United States Agency for International Development

1. Introduction and problem definition

The core objective of this thesis is to examine the economic impact of human recognition for women farmers in Malawi. It outlines the concept of human recognition as facets of poverty and human development and thus, human recognition's instrumental role in economic development for women. Focusing on women farmers, it intersects the provision of human recognition with agricultural activities, a main engine of economic development in sub-Saharan African countries like Malawi. For women farmers in particular, institutional and power dynamics in access to resources like land are crucial to their livelihood. Malawi offers a unique societal arrangement to investigate the effects of non-tangible concepts of human development on overall wellbeing in agrarian households.

Access to productive resources for agricultural use

Agriculture is significant to economic growth in developing countries (Gollin, 2010, p. 3825). For sub-Saharan African countries, agricultural activities are essential to food security, poverty reduction, capital accumulation and economic wellbeing (Doss et al., 2011, p. 4). However, there is low performance in agriculture in several developing countries. This has been linked to restrictive institutional settings and inadequate policies that disadvantage women farmers and constraint productivity (Diao, Hazell, & Thurlow, 2010, p. 1376; Doss et al., 2011, pp. 5–11). Particularly, lack of knowledge on land rights, social norms and structural violence against women hinder efforts to improve women's access to and control of resources. Thus, providing women farmers with greater control of economic resources such as land and other facilities can translate to higher productivity, growth and better nutritional outcome in the household and on a national level.

Several studies outline the link between resource access like land and women's position in the society. Quisumbing et al. (2015, p. 706) note that gender norms and practices define gender power within households, communities/institutions and limits women's socio-economic opportunities, acting as barriers to livelihood investments for women. Access to productive assets facilitate access to other resources and provides a pathway out of poverty (Meinzen-Dick et al., 2011, p. 1). Particularly, women who have access to or owners of productive resources, have better household bargaining power and significantly contribute to food security, sustainable land management and improved children's nutrition (Alkire et al., 2013, p. 71; Meinzen-Dick et al., 2011, p. 18; Mishra & Sam, 2016, p. 360). Mishra and Sam (2016, pp. 360–371) observe that women with more bargaining power are also likely to participate in community development like irrigation projects and soil conservation; and are also likely to invest in human capital such as health, nutrition and education. Thus, policies for equitable land rights equity have the potential to increase women's empowerment and bargaining power in agrarian-based economies (Mishra & Sam, 2016, pp. 360–361).

Diminishing the gender resource gap is a pathway to enhancing women human development and reducing poverty in sub-Saharan Africa. For example, Alkire et al. (2013, pp. 71–91) observes that enabling women to own and control productive resource like land improves their agricultural productivity, self-regards and impacts their psychological wellbeing. In the same vein, Trommlerová, Klasen, and Leßman (2015, pp. 1–3) suggests that material, human and social resources, which are available to individuals in communities play a significant role in human development and empowerment. However, the resources distribution is usually determined by prevailing social norms, which influences women's value recognition and access rights.

The role of societal norms in the resource access rights

Norms[1] are part of societal structure and habits. Social norms address ways by which communes of individuals behave in order to achieve a specific collective interest and as such, seen by

[1] Ben-Ner and Putterman (1998, p. 7) define norms as external actions resulting from the interaction of several actors

Platteau (2006, p. 821) as the values and morals governing societies. Social norms shape intuitive processes and defines actions that are acceptable or unacceptable. Social norms are learned through socialization processes in societal institutions like schools, families and communities. For communal societies, norms that define human actions are influenced by communal values[2] which the community holds collectively (Ben-Ner & Putterman, 1998, p. 7; Platteau, 2006, p. 821). Thus, traditional rural communities, especially agrarian societies, are identified as societies where norm behaviours are predominantly present and often exercised. Rural African societies are often lineage based and are embedded with social process values[3] that are nurtured in every individual from early childhood (Ben-Ner & Putterman, 1998, p. 7; Evers & Walters, 2000, p. 1342; Platteau, 2006, p. 823). Thus, positions like resource ownership or access rights are naturally, distributed through social norms dominant in communities and institutions. Platteau (2006, pp. 821–825) argues that norm-based strategies regarding the control of resources must give way to market forces. This allows agrarian societies to empower all its members and avoid unsustainable equilibriums that exclude vital individuals from contributing meaningfully to economic growth. Therefore, it is imperative to note that the key to overcoming these challenges lie in substantial economic and social mindset shift in the way women are viewed, valued and treated, individually and in the society.

State of the art

Ideally, institutions and policies supporting women farmers are includes designs that sustain resource access, enhance capability functions and facilitate economic services previously beyond

[2] According to Ben-Ner and Putterman (1998, p. 7), norms influence how communities behave collectively for the benefit and can also be seen as arguments of a utility function.

[3] These are norms concerned with the consumption or outcome of others. Platteau (2006, pp. 823–825) argues that norms are used to identify group-focused societies. Characteristics of this type of society includes members that are completely immersed in social totality and been unable to think of themselves as autonomous human beings.

reach. More importantly, Peterman, Billings, and Behrman (2013, p. 30) note that recognition within households and communities for women are crucial components for women's secure ownership and access to productive resources such as land. Castleman (2013, p. 2) notes that development outcomes like poverty reduction and resource access are influenced by intangible dimensions of human development like human recognition. Thus, development outcomes such as reducing gender inequality for women farmers, enabling access to and control of productive resources and improving socioeconomic welfare are heavily impacted by human recognition.

Particularly, human recognition addresses the extent to which an individual is acknowledged by others to be of inherent value (Castleman, 2013, p. 2). For women farmers, it affects empowerment outcomes through its effect on material outcomes like land access, ownership, income or agricultural productivity; and psychological wellbeing (Castleman, 2013, p. 2). Although studies link poverty and economic behaviour to positive recognition with positive effects on wellbeing in general, research detailing how human recognition impacts women and women farmer's ability to access resources like land, and facilitate wellbeing is yet to be carried out. Thus, there is need to examine the influence of human recognition, a multidimensional facet of human development, and how it shapes land access, material outcomes and wellbeing of women farmers.

Extending the theory of human recognition and economic development, this thesis outlines a framework of human recognition in general, estimates a measure of negative human recognition, assesses the impact of negative human recognition on land access, welfare and land use choices using secondary and primary data respectively. It also describes an approach for sampling survey data for development research in rural/developing countries under information and budget constraints.

2. A framework of human recognition

Human recognition is multidimensional. It may be positive or negative and can be received from several sources from three (3) domains of social interaction:

(a) from one's self,

(b) from household relationships and interactions,

(c) from community norms and interactions among individuals in the community (Castleman, 2013, p. 7).

Human recognition plays an instrumental role in recipients' wellbeing as follows (Castleman, 2016, pp. 135–151):

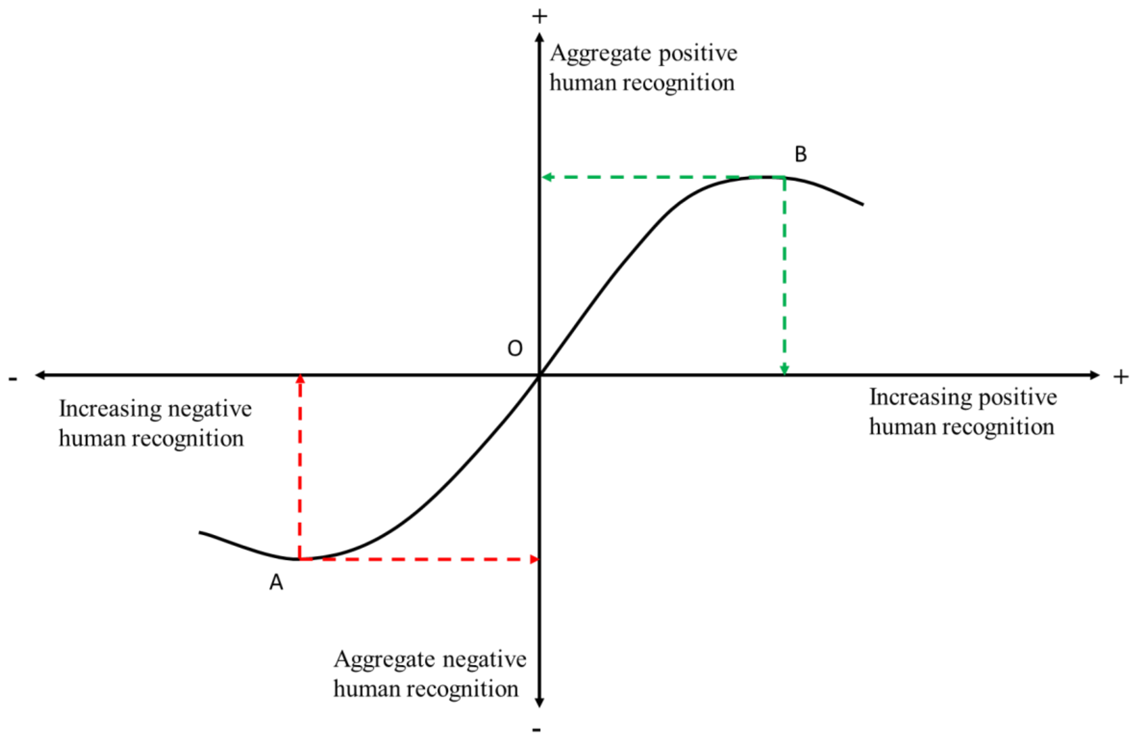
- The quantity of human recognition a person receives has direct impact on their psychological wellbeing. In other words, being viewed as less than human negatively impacts a person's wellbeing.
- Human recognition facilitates changes in dignity which indirectly affects wellbeing in all forms.
- The quantity of human recognition a person receives affects their actions with significant impact on material outcomes.
- Human recognition provision has significant impact on actions of the provider which in turn, impacts the wellbeing of the recipient in a feedback loop. For example, when individuals in the society provide negative human recognition to women, it may manifest as domestic violence or discrimination which negatively impacts the physical wellbeing of women or the nutritional wellbeing of their households.

For women farmers, access to and control of resources like land and autonomy has direct and indirect effects on overall wellbeing in the sense that it is plausible that women farmers that have higher human recognition to have a higher level of wellbeing. Castleman (2013, p. 10) makes a large distinction between human recognition recipient and providers and notes that the optimal total quantity of human recognition accruing to an individual, i, should fulfil the following properties. It should:

1) have weak essentiality,
2) have monotonicity,
3) have diminishing marginal returns of additional human recognition,
4) have increasing marginal effect on magnitude of received human recognition,
5) be non-decreasing in function and
6) have diminishing marginal effects of second order differentials of the function (See Castleman (2013, pp. 1–20) for the full derivation of human recognition properties).

Thus, if the quantity of human recognition provided to a group of individuals satisfy properties 1-6, additional positive human recognition provision should lift individuals up from a point of negative human recognition (AO) to a point of higher positive human recognition (OB) as shown in the Figure 2-1 below:

Figure 2-1 Model of Human recognition Reception



Source: Own

Because human recognition is provided and received in spheres of public and private interactions, communities and individuals may determine the quantity of human recognition they wish to provide to others and thus, its reception may be influenced by several exogenous factors (Castleman, 2013, p. 15). For women farmers in sub-Saharan Africa, these factors are mostly social norms, gender and social capital; and significantly impact how much human recognition they receive in the society. However, it is important to note that in addition to these exogenous factors, there are benefits and transactions costs associated with receiving human recognition. For example, a woman farmer who chooses to improve her human recognition or receives better human recognition from providers inside/outside the community (development programs, aid initiatives etc.) may incur transaction costs like social ostracization, exclusion and/or further poverty in the community, if the recognition received goes against set societal norms. On the other hand, benefits like positive household wellbeing may increase with increasing benefits of positive human recognition, overcoming these transaction costs. Thus, it is necessary to model a profit profile of human recognition reception, outlining the benefit and transaction cost involved in receiving human recognition in general.

The profit profile of human recognition reception

Let $r_{i\leftarrow p}$ be the quantity of human recognition received by individual, i, from a host of providers $p = 1 \cdots n$. Note that for simplicity, quantity dependency on the providers[4] cost-benefit analysis is supressed. From these providers, individual, i, selects the quantity of human recognition that maximizes aggregate benefit and minimizes cost as follows:

$$B(r_{i\leftarrow p}) = \lambda(r_{i\leftarrow p}) + \mathrm{I}(R_i, r_{i\leftarrow p}) \tag{2.1}$$

Where $\lambda(r_{i\leftarrow p})$ is the marginal benefits accruing to individual, i, as the recipient, with λ as the slope parameter. R_i is the baseline human recognition level of individual, i, and $\mathrm{I}(R_i, r_{i\leftarrow p})$ represents all possible benefits individual, i, could gain from accepting human recognition from all providers. For example, communities with working formal and informal institutions that support land access rights for women farmers can increase household productivity and community food security and thus, provide women with higher human recognition.

In accepting human recognition from these providers, individual, i, incurs transaction costs, $C(r_{i\leftarrow p})$ as follows:

$$C(r_{i\leftarrow p}) = \alpha r_{r\leftarrow p}^2 + \beta r_{i\leftarrow p} \qquad where\ \alpha, \beta > 0 \tag{2.2}$$

[4] For ease of interpretation, providers will be used to refer to households, programs, organizations, communities, individuals or even one’s self providing recognition to others.

The term, $\alpha r_{r\leftarrow p}^{2}$, denotes the fixed, positive marginal cost which individual, i, incurs when accepting positive or negative human recognition. They may involve time (giving up leisure time for example), expended efforts/energy and other resources (Castleman, 2013, p. 17). $\beta r_{i\leftarrow p}$ presents the variable costs (investment costs) of receiving human recognition. These investment costs can be either positive or negative.

Consequently, individual, i, determines the quantity of human recognition to accept by maximizing perceived benefits, $B(r_{i\leftarrow p})$ and minimizing perceived costs, $C(r_{i\leftarrow p})$ in a simple linear profit equation as follows:

$$Max\ \pi\left(r_{i\leftarrow p}\right) = \lambda r_{i\leftarrow p} + r_{i\leftarrow p}\imath(R_i) - \alpha r_{i\leftarrow p}^{2} - \beta r_{i\leftarrow p} \tag{2.3}$$

Solving equation (2.3) for optimal human recognition received, $\lambda r_{i\leftarrow p}{}^{*}$, yields:

$$\lambda r_{i\leftarrow p}{}^{*} = \frac{(\lambda + \imath(R_i)) - \beta}{2\alpha} \tag{2.4}$$

The term above shows that the optimal human recognition, $\lambda r_{i\leftarrow p}{}^{*}$, received/accepted by individual, i, depends on their overall benefits minus the cost of accepting/receiving human recognition from providers, all weighted by their positive fixed cost. In other words, the marginal benefit of receiving human recognition is positive, that is greater than zero, the overall stock of human recognition accruing to that individual will also increase and vice versa (Castleman, 2013, p. 21).

Since the decision to accept or receive human recognition is influenced by benefits and transaction costs on the side of the recipient, several equilibrium points for human recognition may exist for high, neutral or low human recognition levels within households and communities (Castleman, 2013, p. 21). These equilibrium points may provide feedback effects on members of the community. For example, if other community members provide positive human recognition to women farmers who are community members too, by altering formal and informal institutions that restrict land access, it can create positive feedback effects on these members in several forms such as better food security and improved poverty outcomes.

Before modelling the impact of human recognition on wellbeing of women farmers, it is important to account for women empowerment domains where human recognition has direct and indirect influence. In line with Alkire et al. (2013, p. 79), the ability to make choices in agricultural production as well as decide on who controls access and ownership of resources can be enhanced by human recognition. Control of and use of income generated from land activities reflects another key domain of empowerment with large impact from human recognition while leadership and community participation show the level of social inclusion that human recognition could provide in the community. Given the above, the influence of human recognition provision on the wellbeing of a women farmer is modelled below.

The Influence of Human Recognition on Wellbeing of a Woman Farmer.

Let utility function, U_w, of a woman farmer, w, be derived from a vector of wellbeing factors, $z()$. For simplicity, let her utility be a function of two wellbeing factors, land access for agricultural activities, $z(L_{ag})$, and household nutritional wellbeing, $z(N_{hh})$. The influence of human recognition on her utility is given as:

$$U_w = U\left(L_{agw}, N_{hhw}, \bar{R}_w, R_{w\leftarrow p}\right) \quad (2.5)$$

Where her land access for agricultural activities is L_{agw}, her household nutritional wellbeing is N_{hhw}, $\bar{R}_w$ is her baseline stock of human recognition and $R_{w\leftarrow p}$ is the human recognition received from providers. Land access for agricultural activities, L_{agw}, and household nutritional wellbeing, N_{hhw} is determined as:

$$L_{agw} = L_{agw}\left[L_{agw}, \bar{R}_w, R_w\right] \quad and \quad N_{hhw} = N_{hhw}\left[N_{hhw}, \bar{R}_w\right] \tag{2.6}$$

In equation (2.6), the human recognition received from providers, $R_{w\leftarrow p}$, is included in the land access function to outline the impact, an additional quantity of human recognition can have on women farmers' ability to access land resources for production. Although human recognition received from providers, $R_{w\leftarrow p}$, can significantly influence household nutritional wellbeing, N_{hhw}, it is not included in the nutrition function at the first stage equation above because it is assumed that human recognition effects on nutritional wellbeing are lagged and is also endogenous to quantity of agricultural land and productivity in farm women households. i.e., the effect of human recognition on nutritional wellbeing from one unit increase in human recognition provision is not captured in the first year cycle of land access implementation but in the second or later years as a positive or negative consequence of land access.

The cost and benefits of human recognition on the utility of a woman farmer is taken from the human recognition profit function (equation (2.3)) as follows:

$$\pi\left(R_{w\leftarrow p}\right) = \lambda R_{w\leftarrow p} + R_{w\leftarrow p}\iota\left(\bar{R}_w\right) - \alpha R_{w\leftarrow p}^2 - \beta R_{w\leftarrow p} \tag{2.7}$$

Where $\pi\left(R_{w\leftarrow p}\right)$ is the profit function of receiving human recognition for the woman farmer, $\lambda R_{w\leftarrow p} + R_{w\leftarrow p}\iota\left(\bar{R}_w\right)$ represents all benefits accruing to the woman farmer from receiving human recognition and $\alpha R_{w\leftarrow p}^2 - \beta R_{w\leftarrow p}$ represents the all transaction costs incurred from receiving human recognition[5]. According to Castleman (2013, p. 22), equation (2.7) above is a

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[5] This is because the feedback effects a positive agricultural policy receives from providing human recognition is assumed to be very small or dispersed because most policies are community or nationally-based and also target relatively large population of recipients (See Castleman (2013, p. 20)) during first implementation. Subsequent policy interactions may increase the extra

sub-utility function in because an individual's own stock of human recognition, although an endogenous variable in the profit maximization model, be treated as exogenous in the utility maximization function.

Solving for optimal human recognition received, for a woman farmer from the equation (2.7) above yields

$$R^{*}_{w\leftarrow p} = \frac{\left(\lambda + \iota(\bar{R}_w) - \beta\right)}{2\alpha} \tag{2.8}$$

In modelling the total utility function of a woman farmer, equation (2.5) is transformed into four (4) sub-utility functions namely, (1) the sub-utility forms of land access for agricultural activities and (2) household nutritional wellbeing, (3) a simple linear function, $U\left(\bar{R}_w\right) = \mu\bar{R}_w$, that highlights the effect of human recognition on other forms of wellbeing (e.g. psychological) with impact on her utility, and (4) her profit function.

Incorporating all four (4) sub-utility forms into the general utility function of a woman farmer, U_w, yields:

$$U_w = u_{wlag}\left[L_{ag}\left(L_{agw}, \bar{R}_w, R_{w\leftarrow p}\right)\right] + u_{wnhh}\left[N_{hhw}\left(N_{hhw}, \bar{R}_w\right)\right] + \mu\bar{R}_w + \pi(R_{w\leftarrow p}) \tag{2.9}$$

Where u_{wlag} and u_{wnhh} are sub-utility forms of land access for agricultural activities and household nutritional wellbeing, $\mu\bar{R}_w$ is the sub-utility for effects of human recognition on other

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benefits of that policy; however, this also requires recognition provision from the recipients in the first policy interaction – the women farmers to act as recognition providers to the policy. This is possible when the women farmers acknowledge the relevance of certain development policies in their communities which – in turn - increase the desirability and prestige of such policies in other communities.

forms of wellbeing and $\pi\left(R_{w\leftarrow p}\right)$ is the profit function linked to receiving human recognition. Equation (2.9) above implies that a woman farmer's total utility can be derived from the utility she gets from accessing land for use, her household nutritional wellbeing, the direct effect of human recognition on other forms of wellbeing and the profit gotten from receiving human recognition from providers.

Substituting $\pi\left(R_{w\leftarrow p}\right)$ with $R^{*}_{w\leftarrow p}$ and solving for the first order differentials yields

$$\frac{\partial U_w}{\partial \bar{R}_w} = \frac{\partial U_w}{\partial L_{agw}} \frac{\partial L_{agw}}{\partial \bar{R}_w} + \frac{\partial U_w}{\partial N_{hhw}} \frac{\partial N_{hhw}}{\partial \bar{R}_w} + \mu + \frac{\iota}{2\alpha}\left(\lambda - \beta + \iota \bar{R}_w\right) \quad > 0$$

(2.10)

Where $\mu, \iota \; > \; 0$, ∂U_w is the total expression of marginal utility a woman farmer derives from changes in her baseline stock of human recognition, $\bar{R}_w$, and $\iota \bar{R}_w$ highlights the marginal benefits of human recognition provision on her baseline human recognition levels. Equation (2.10) above illustrates that human recognition has a direct influence on land access and household nutritional wellbeing of a woman farmer, which greater than zero i.e.,

$$\frac{\partial U_w}{\partial L_{agw}} \frac{\partial L_{agw}}{\partial \bar{R}_w} > 0 \quad and$$

(2.11)

$$\frac{\partial U_w}{\partial N_{hhw}} \frac{\partial N_{hhw}}{\partial \bar{R}_w} > 0$$

(2.12)

In addition, human recognition has a positive effect on other forms of wellbeing i.e., $\mu > 0$.

Finally, human recognition received from providers has an indirect effect the wellbeing of the woman farmer through the cost benefit outcome i.e. $\frac{\iota}{2\alpha}\left(\lambda-\beta+\iota\bar{R}_w\right) \quad > 0$

(2.13)

Human recognition for women farmers in Malawi

For this research on the impact of human recognition for wellbeing, a case study for Malawian women farmers is selected. The reasons for the country case choice are explained below.

Women farmers are most hit by food insecurity in Malawi. However, they are severely constrained as they lack ownership and access to the factors of production like land. Government of Malawi [GoM] (2006, p. 40) observed that women in Malawi are more marginalized when compared Malawian men. Furthermore, women's lack of empowerment in Malawi is linked to several factors including gender-based violence towards women (GoM, 2006, p. 39). This, often, enhances other factors that limit women from participating in economic activities that can lead to empowerment (GoM, 2006, p. 51). For instance, from 2004-2010, Ministry of Gender, Children, Disability and Social Welfare [MoGCDSW] (2014, p. 14) reported that women in rural areas grew poorer as a result of inadequate access to land and land discrimination based on gender and socio-economic status. In addition, studies show that development policies in Malawi do not sufficiently address the situation of gender inequality from a human right and human recognition perspective. This is relevant if the development policy aim is to improve levels of specific components of wellbeing through human recognition and facilitate sustainable human and agricultural development in Malawi.

In 2012, Malawi adopted a National Land Policy, with the aim to increase equitable access to land and land tenure security. However, the policy is criticized for its inadequacy in protecting women rights to land (MoGCDSW, 2014, p. 40). Despite existing policy frameworks such as the Malawi Poverty Reduction Strategy (MPRS I and II) and the Malawi Economic Growth Strategy

(MEGS), gender inequality in access to and control of land resources as well as gender based division of labour continue to occur. Weak policy coordination and implementation of gender oriented policies has also contributed to weak women empowerment in Malawi especially in agriculture. One of the main reasons are the still dominant patriarchal decision making patterns and an embedded culture that reinforces gender inequalities (African Development Fund [ADF], 2005, p. 4). The UN Women, UNDP-UNEP, PEI Africa, and the World Bank 2015 study on gender gap in productivity in Malawi notes that women farmers in Malawi, have on average, lower levels of education and lower access to land resource. In Malawi, about 70% of the women farmers are widowed, divorced or separated compared to 3% for men and this influences land ownership and access due to current prevalent gender norms. As women are key in food security and development, it is relevant to investigate, how the perception of women as economic agents and as humans with equal rights can become an important driver economic development.

Research Objectives

The previous sections outline the importance of land access and ownership for women farmers, linking it to food security, human and economic development for rural communities. Incorporating human recognition into institutions present in rural communities, these sections outline how human recognition can facilitate material and other forms of wellbeing for women farmers. It notes that in Malawi, a landlocked, agrarian, sub-Saharan east African country, gendered institutions influence how women farmers own or access land. However, the nexus where poverty reduction, human development, land resource ownership and access intersect, are yet to include intangible components of development like human recognition.

To that end, this thesis focuses on human recognition principles modeled above, derives a measure of human recognition and extracts applicable insights for women farmers using Malawi as a case study. The following research objectives support the aim of the research thesis as follows:

Research Objectives

Using nationally representative secondary data from several time waves, this thesis:

1) Assesses the indicators of multidimensional (negative)human recognition (deprivation) and examines these indicators with the domains of interaction for women namely: self, household, community/institution. Using these indicators, it develops an index of multidimensional (negative) human recognition (deprivation) and extracts various measurement parameters that highlight the width and breath of human recognition deprivation for women overall and in these domains.
2) Investigates the determinants of human recognition deprivation for women in Malawi compared to Peru with negative human recognition, highlighting negative human recognition as an intangible development concept that affect women as a class.
3) Examines the effect of negative human recognition on land access and household wellbeing for women farmers in Malawi.

It is also important to reconcile evidence extracted from secondary empirical analysis with a sub-sample analysis from primary data. The aim is to compare the estimates of negative human recognition in the representative national data with that observed in the primary sample for women farmers in Malawi. As a result, the thesis:

4) Outlines a multilevel sampling approach for survey data, applied in Malawi to collect relevant data on indicators of human recognition, socio-economic and social demographic information of women farmers.
5) Examines the effect of self, household and institutional human recognition on responsible land management and land use choices for sampled Malawian women farmers.

Thus, the following research hypothesis are investigated in support of the research objectives outlined above.

<u>Research hypothesis (1)</u>: Research hypothesis (1) outlines the sub-hypothesis for research objective (1), as follows:

(a) Multidimensional human recognition deprivation index can be derived from indicators of humiliation, dehumanization, violence and lack of autonomy for women within three social domains of interaction namely: self, household, and community.

(b) The methodology (Alkire-Foster method of multidimensional poverty counting) used to develop the multidimensional human recognition deprivation has a range of robust properties which allows in-depth analysis on the width and breath of deprivation through the headcount ratio, deprivation intensity as well as decomposition by domains and sub-groups (region and farm worker) for women.

(c) This methodology is also robust to a host of measurement tests and satisfies the various structural properties of human recognition provision as outlined in the first part of the theoretical section.

Paper 1 and parts of paper 2 under chapters 3 and 4, address these sub-hypotheses.

<u>Research hypothesis (2)</u>: Research hypothesis (2) outlines the sub-hypotheses for research objective (2), as follows:

(a) Using the Alkire-Foster method, a dichotomous censored count of deprived women (1 = deprived, 0 = otherwise) can be established for Malawi and Peru.

(b) There are notable association between certain social-demographic and socioeconomic factors and human recognition deprivation for women.

(c) Comparatively, these social-demographic and socioeconomic factors are significant and consistent across Malawi and Peru.

Paper 2, under chapter 4, addresses these sub-hypotheses.

Research hypothesis (3): Research hypothesis (3) ties the following sub-hypotheses to research objective (3), as follows:

(a) Negative human recognition leads to lower access to land for women farmers in Malawi.

(b) Negative human recognition has a detrimental effect on wellbeing for women farmers in Malawi.

Paper 3, under chapter 5, addresses these sub-hypotheses.

Research hypothesis (4): Research hypothesis (4) outlines the sub-hypothesis for research objective (4), as follows:

(a) Multilevel design involving random spatial sampling with GIS and systematic random sampling with GPS and PDAs, can be used to generate robust data from women farmers in an information and resource constrained context.

Paper 4, under chapter 6, addresses this sub-hypothesis.

Research hypothesis (5): Research hypothesis (5) outlines these sub-hypotheses for research objective (5), as follows:

(a) Land use behavior is influenced by latent self/household and institutional human recognition.

(b) Latent self/household and human institutional recognition influence women farmers' community participation.

Paper 5, under chapter 7, addresses these sub-hypotheses.

Structure of the dissertation

This thesis is a cumulative collection of peer-reviewed publications: published and forthcoming (See Figure 2-2); and is made up of a total of five (5) original research articles/contributions. This section outlines the content of each contribution and presents the structure of the thesis.

Paper 1 (chapter 3) employs the Alkire and Foster method of multidimensional poverty counting to estimate a multidimensional human recognition deprivation index (HRDI). Using indicators of humiliation, dehumanization, violence and lack of autonomy for women within three social domains of interaction: self, household, and community, the contribution illustrates that human recognition levels of women in Malawi is measurable within the domains of interaction. By setting different cut-offs by indicators and weights by domain, the contribution examines the varying indicator and domain effects on overall human recognition deprivation

Paper 2 (chapter 4) presents the analysis on the social-demographic and socioeconomic determinants of human recognition deprivation for women in Malawi and Peru using the dichotomous censored count of deprived women (1 = deprived, 0 = otherwise). This contribution employs logistic regression analysis to isolate relevant determinants in Malawi and Peru and examines their marginal contribution in the models analysed for both countries.

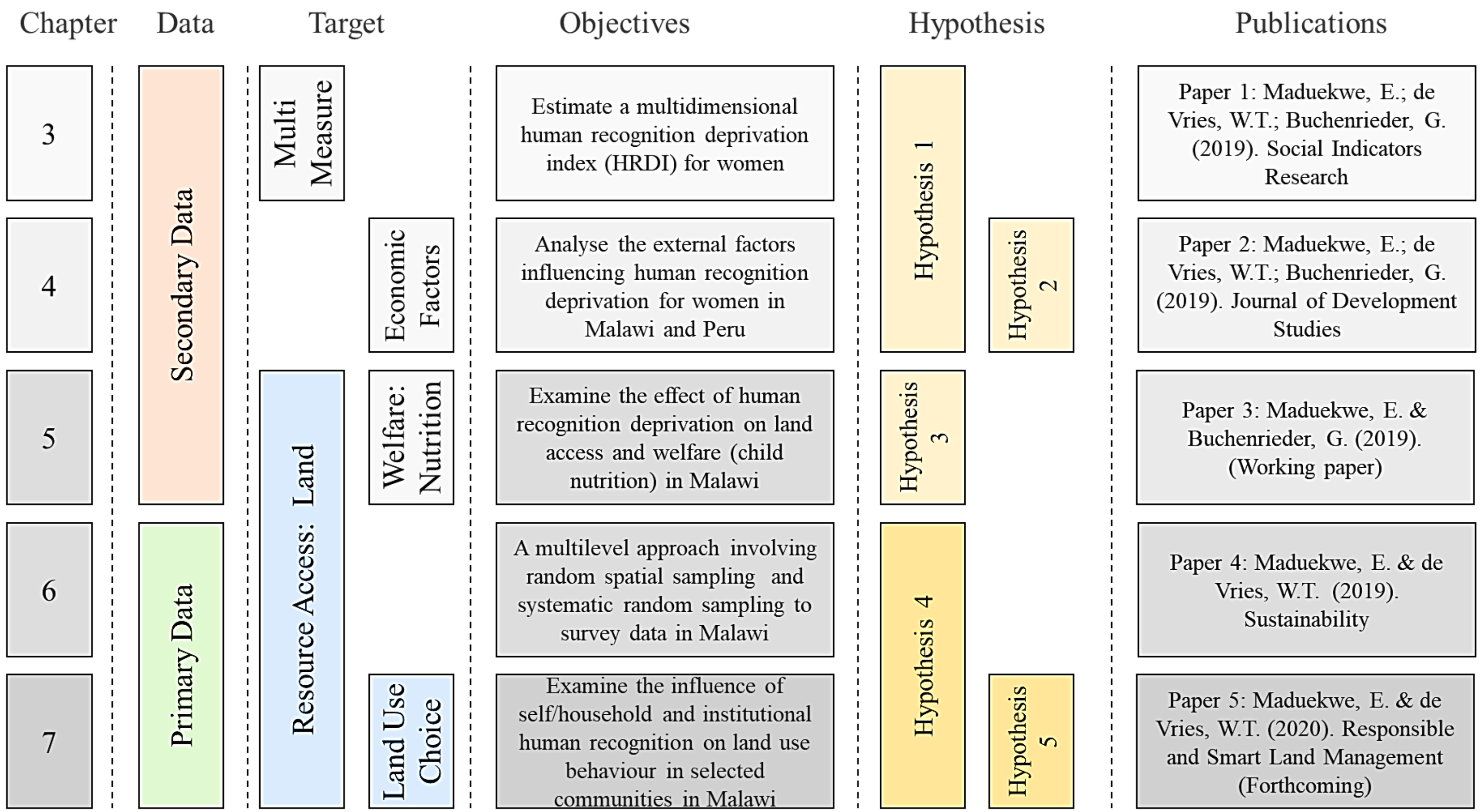
Paper 3 (chapter 5) models negative human recognition and household wellbeing in the presence of non-cooperative household bargaining and non-viable exit options. Using ordinary least squares regression and accounting for the endogenous nature of negative human recognition with instrumental variable regression, this contribution highlights the trade-offs faced by women farmers in accessing land in Malawi.

Paper 4 (chapter 6) describes a survey sampling approach for development data for collecting information on human recognition and other land use outcome. This approach is applicable to developing country where information and budget constraints exist. This contribution describes a multilevel sampling method using spatial sampling (GIS) on ArcGIS and systematic random sampling with random walk (PDAs with GPS). It also highlights the present challenges of investigating human development outcomes in a developing country context.

Paper 5 (chapter 7), uses primary survey data to investigate the influence of positive human recognition on land use choices for women farmers in surveyed communities/villages in Malawi.

This contribution models the impact of positive human recognition on land use choices and community discourse in Malawi using structural equations. It also outlines policy recommendations for land administrators who wish to improve women’s human recognition and recognition as land managers in these communities in Malawi.

Figure 2-2 Overview of dissertation structure



3. Measuring Human Recognition for Women in Malawi using the Alkire-Foster Method of Multidimensional Counting

This chapter is published as follows:

Maduekwe, E.; de Vries, W.T.; Buchenrieder, G. (2019). Measuring Human Recognition for Women in Malawi using the Alkire Foster Method of Multidimensional Poverty Counting. Social Indicators Research 95 (11), 1-20, https://doi.org/10.1007/s11205-019-02175-z.

Abstract

Policy indicators rarely account for the contribution of societal inter- and intra-personal interactions to economic development. We propose an index of multidimensional Human Recognition Deprivation (HRD), which measures to what extent individuals (e.g., women) are viewed and valued as human beings.

Based on Castleman's Theory of Human Recognition and Economic Development, we employ the Alkire-Foster method of multidimensional poverty counting to construct a HRD index. The Index is based on indicators of humiliation, dehumanization, violence, and lack of autonomy within three domains of interaction namely: the self, household, and community domains. Similar to multidimensional poverty, we extract the deprivation headcount ratio, deprivation intensity, and the overall deprivation index.

The Alkire-Foster method allows us to identify human recognition deprivation within and across domains of interaction. The methodology has a range of robust properties including decomposing by domains and sub-groups (e.g., female farmers and off-farm women). As a policy tool, it allows policy investigators to set different domain cut-offs and weights to identify crucial policy fields and populations for intervention. We develop the index for women using data from Malawi.

Keywords: Human recognition, violence, Malawi, gender equality, multidimensional measurement

Introduction

The last decades have seen research aiming at better understanding the factors that contribute to poverty[6]. Apart from access to education and income creating activities, Sen (1988, pp. 269–294; Sen, pp. 151–166) proposed strengthening the freedom of choice, empowerment and social capital while Castleman (2013, p. 2) emphasized additional intangible concepts like human recognition. Several studies link positive recognition in society to economic development (Doepke & Tertilt, 2014, p. 1; Kabeer, 1999, p. 435). However, related concepts such as human recognition and its contribution to poverty have not been clearly examined and measured (Castleman, 2011, p. 3, 2011, p. 3, 2012, p. 4, 2013, 1; Schweiger, 2015, p. 143). Castleman (2016, p. 136) defines human recognition as the extent to which an individual is viewed and valued by others as well as treated based on this value. He also models how provision of recognition could improve not only recipient wellbeing but contribute to aggregate economic development.

This contribution employs the Alkire and Foster method of multidimensional poverty counting, referred to as the Alkire-Foster method, to estimate a multidimensional human recognition deprivation index (HRDI). We use indicators of humiliation, dehumanization, violence and lack of autonomy for women within three social domains of interaction namely: self, household, and community, in line with Castleman (2016, pp. 136–140). We illustrate the human recognition of women in Malawi[7] using the pooled cross-sectional Demographic and Health Survey (DHS) datasets for 2004, 2010, and 2015.

In addition to keeping track of the extent to which women are viewed, valued and treated, the HRDI sets itself apart in the following ways. First, it identifies the number of deprived persons in the

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[6] Poverty reflects monetary and non-monetary deprivation. In this paper, we focus on human recognition deprivation and argue that poverty is worsened by lack of recognition.

[7] As this contribution is not country analysis of Malawi, a causal analysis of human recognition deprivation on women's socioeconomic outcomes is beyond its scope.

population as well as the intensity at which they are deprived. Second, it combines already available indicators of humiliation, dehumanization, violence, and lack of autonomy, which are represented in other countries, therefore an international comparison of the HRDI would be possible. Third, setting different cut-offs by indicators or weights by domain allows for the examination of varying indicator or domain effects on overall human recognition deprivation. Finally, policy makers who wish to improve human recognition levels for women in general, could investigate specific domains or sub-populations of women using different domain weights and cut-offs for targeted policy outcomes.

We present our article as follows: Section 2 highlights the theory and conceptual framework of human recognition. Section 3 explains our methodology: the Alkire-Foster method and how it is used to estimate human recognition deprivation. We test the HRDI using data from Malawi and present the results in section 4. Section 5 and 6 discusses and concludes by presenting a number of policy implications based on these findings.

Theoretical Framework

Theory of Human Recognition

The theory of recognition has roots in social, moral-philosophical and socio-political outlooks (Am Schmidt Busch, 2008, p. 574; Honneth, 2001, p. 44; Laitinen & Ikäheimo, 2011, p. 4). For Laitinen and Ikäheimo (2011, p. 5), the Hegelian[8] understanding of recognition is the core of psychological, social and institutional structures in the society. In societies with recognition, individuals are able to build and maintain healthy personalities, self-awareness and improve the ethical qualities of social relations through including people that are different from themselves into their sphere of social and economic life as equals. Laitinen and Ikäheimo (2011, p. 8) understand recognition to involve identification and acknowledgement of intrinsic valuing, plus further applying recognition to persons and groups of persons in the interpersonal sense. Castleman (2016, p. 135) further defines human recognition as "[…] the extent to which an individual is acknowledged by others to be of inherent value by virtue of being a fellow human being […]".

Honneth (2001, p. 47) developed a "tripartite division" of recognition with an interpersonal viewpoint pertaining to societal injustice, which includes respect and self-/social-esteem. Building on Honneth (2001, pp. 43–55), Schweiger (2015, p. 144) defines respect as the right that humans owe themselves as equal agents and self-/social-esteem as the notion that everyone deserves to be recognized for their contribution to a shared agenda. Although Castleman (2016, pp. 140–142) conceptually distinguishes between respect, dignity, empowerment and social capital, we posit that these concepts are not distinct but ontologically interwoven[9]. When rights denial and social exclusion exists, human beings suffer

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[8] See Hegel (1991); Hegel and Miller (1977) for detailed insight.

[9] Castleman (2016, p. 140) argues that respect for an individual's basic rights as human being may not go hand in hand with respect for an individual's skills or productive abilities. Dignity is defined by Castleman (2016, p. 141) as "[…] a quality or feeling that an individual possesses or experiences or that others attribute to her […] ". Kabeer (1999, p. 437) outlines empowerment as "[…] the

indignity and injustice, which strips them of recognition as members of the community (Honneth, 2001, pp. 48–49). The antidote is for individuals to provide positive recognition in which there is acceptance and social regard of other individuals' abilities. Recognizing individuals takes on positive orientation because of assurance and appreciation for their attributes or achievements (Honneth, 2001, p. 50). Honneth (2001, p. 50) further notes that without an assumed measure of self-/social-esteem, a protected autonomy and a belief in one's abilities, it will be impossible to achieve an effective process of self-actualization. This is because self-actualization requires the freedom to choose and to pursue one's aim in life in a context not only free of external obstacles but also free of internal pressure or psychological hindrances (Honneth, 2001, p. 51). Thus, positive self-actualization is achieved through recognition because it depends on the preconditions acquired only through cooperation and interactions with other fellow human beings.

Need for Human Recognition

Given that human recognition is undeniably centered on people and shapes the basis of our societies, the importance of measuring it cannot be overstated. Poverty, especially in agrarian sub-Saharan Africa, is entrenched within social struggles and connected to many socio-economic factors including human recognition and/or gender equality (Schweiger, 2015, p. 145). These factors influence poverty and are therefore relevant for its measurement. Nevertheless, human recognition is neither embedded in poverty measure nor in economic development strategies. Generally, poverty is embedded in modern societies by virtue of its connection to the social system and the systemic disregard for certain groups in society (Schweiger, 2015, p. 146). According to Sen (1988, pp. 269–294, 2005, pp. 151–166) , the effect of absolute poverty, such as lack of access to food, shelter, or education, is important

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expansion of people's ability to make strategic life choices, particularly in contexts where this ability had been denied to them […]".Castleman (2016, p. 142) defines social capital as "[…] an instantiated set of informal values or norms shared among members of a group that permits them to cooperate with one another […]".

because of its link to self-/social-esteem[10], which is a key facet of human recognition. This connection makes poverty a direct attack on ones' freedom and capabilities and an impediment to one's empowerment. For Kabeer (1999, p. 437) disempowerment is denial of choice and is directly associated with poverty because it often hinders one's ability to make meaningful life decisions. Schweiger (2015, p. 147) argues that poverty can then be regarded as a form of recognition deprivation in which experiences of social relations are impossible to achieve or completely reshaped. Am Schmidt Busch (2008, p. 574) observes that historically the core institution of society views the distribution of self-/social-esteem on the principle of achievements, a function of individuals' application of capabilities. Individuals respect and recognize each other because they share the same autonomy and the institutionalization of legal equality; measuring each other on the basis of achievements that are of value to the society (Am Schmidt Busch, 2008, p. 575). Thus, experiencing misrecognition of any kind violates the core conditions of societal inclusion – a state of being that enables people to walk as equals among their peers – and as such, contributes to poverty (Schweiger, 2015, p. 147). Arguably, if the distribution of self-/social-esteem is linked to the principle of one's achievements, then human recognition must be interwoven within the domains of empowerment internally, through one's agency[11] and achievements, and externally, through influence on choice. Naturally, such intangible components are very challenging to measure (Castleman, 2011, p. 3; Kabeer, 1999, p. 436), however, it is crucial that human recognition is understood as a multidimensional concept.

We examine human recognition for women within the domains of intra- and inter-personal space (Laitinen & Ikäheimo, 2011, pp. 8–9). Castleman (2011, p. 6, 2013, pp. 6–7) outlines the various sources of human recognition and highlights three primary domains of interaction, where human

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[10] Honneth (2001, p. 50) argues that without self-/social-esteem, it will be impossible to achieve an effective process of self-actualization and freedom to choose and pursue one's aim in life.

[11] Kabeer (1999, pp. 436–439) defines agency as "[…] the ability to define one's goals and act upon them […]".

recognition can be given and received: (a) relationships with one’s self or as an individual, (b) interactions/relationships among individuals in the household, and (c) institutional/community interactions (see Table 1). It is important to note that human recognition in the institutional domain has also been highlighted by Laitinen and Ikäheimo (2011, p. 10) as institutional recognition[12]. They argue institutional recognition is non-interpersonal in nature and thus, does not fit well with Honneth (2001, pp. 43–55) definition of recognition who considers recognition as love, respect, and justice in all domains of life and interaction. Obviously, human society is made up by social domains encompassing the private and public beings as well as relationship-flows within these spheres. So, exclusion of institutional recognition will result in an incomplete representation of the multidimensional nature of recognition. Laitinen and Ikäheimo (2011, p. 10) and Castleman (2013, p. 7) argue that a full picture of the effects of human recognition takes into consideration the needs of the social world in a way that matches the multidimensionality of poverty to domains of human recognition for self (individuals), households, and institutions/community.

Role of Gender-Violence and Power in Depicting Human Recognition for Women

Several studies have identified links between economic behavior and receipt of regards from others with the result that positive (negative) recognition has a significant impact on the socio-economic position of the poor and marginalized (Castleman, 2013, p. 3). For instance, violence against women is a manifestation of negative recognition that hinder women from achieving choice equality or full enjoyment of rights within the society (Bisika, 2008, p. 1885). Heise, Raikes, Watts, and Zwi (1994, p. 1165) outline violence against women to include a host of harmful behaviors. Particularly, “[…] violence against women includes any act of verbal or physical force, coercion or life-threatening deprivation, directed at an individual woman or girl that causes physical or psychological harm,

[12] According to Laitinen and Ikäheimo (2011, p. 10),institutional recognition focuses on persons as bearers of institutional powers, e.g., the police or government. However, these bearers are human agents and thus also transact positive/negative human recognition.

humiliation or arbitrary deprivation of liberty that perpetuates female subordination […]" (Heise et al., 1994, pp. 1165–1166).

Gender-based violence is recognized as an important human-right violation by international organizations (Fidan & Bui, 2016, pp. 1075–1076) because of its negative effect on women's economic status. Bisika (2008, p. 1884) observes that in Malawi, women bear the brunt of gender violence such as abuse, assault and economic negligence because of social and cultural beliefs. Similarly, Hunnicutt (2009, pp. 553–555) argues, from a feminist theory perspective, that violence against women is a result of social structural conditions, ideologies, and power dynamics especially within patriarchal systems in the domains where individuals interact. As outlined by Heise et al. (1994, p. 1165),violence against women as human recognition manifestations, albeit negative, relates to women as a group within the society. Therefore, the role of violence in depicting recognition compasses not only individual and household manifestations, but structural and institutional forms of discrimination which women experience as class.

One can also relate human recognition to the concept of power and autonomy. Kabeer (1999, p. 436) links empowerment and thus recognition to power by defining power as "[…] the ability to make choices […]". Kabeer (1999, p. 440) points out that the using of achievements to measure empowerment draws attention to the role of choice in the exercise of power. That is, human recognition deprivation disempowers women, stripping women of choices. Since the concept of choice is an external manifestation of empowerment through an internal reception of recognition, respect and self-/social-esteem, it is then, necessary to examine the role of violence, power, and autonomy in depicting human recognition levels for women.

Methodological Approach to Measure Human Recognition

There are challenges in measuring intangible components such as human recognition (Castleman, 2011, p. 8). One way to address this issue is using indicators that capture specific recognition transactions[13]. Several scholars have undertaken efforts to develop measures of intangible concepts like empowerment and wellbeing (Diener & Biswas-Diener, 2005, pp. 125–140; Graham & Pettinato, 2005, pp. 141–175; Malhotra & Schuler, 2005, pp. 71–88; Mason, 2005, pp. 96–102; Pillarisetti & McGillivray, 1998, pp. 197–203; Trommlerová et al., 2015, pp. 1–15), social capital (Knack & Keefer, 1997, pp. 1251–1288), and human recognition (Castleman, 2011, pp. 18–30, 2012, pp. 1–68, 2013, pp. 2–44, 2016, pp. 135–151). Yet, to objectively measure human recognition across domains of interaction, a framework of context-specific indicators is required. "Who is identified as recognition deprived" and "how many domains one needs to be deprived in to be considered human recognition poor", requires a method for isolating identification indicators and combining these indicators into a composite index. For instance, Castleman (Castleman, pp. 1–81; 2012, pp. 1–68) assesses the role of human recognition among malnourished HIV-infected adults in Kenya using food supplementation and medical treatment as a recognition-improvement intervention and found that six months of food supplementation had a significant effect on human recognition. Castleman (2011, pp. 1–81) also looks into the effect of human recognition on nutritional wellbeing of women in India. His results show that human recognition has a significant positive and independent effect on the nutritional status of women. In both studies, exploratory factor analysis was applied across the domains of recognition to build a composite index that measures the aggregate level of human recognition. Weighted sums of recognition levels received in each domain are added to create a final measure of recognition.

It is important to note that factor analysis works on the assumption that measurable and observable indicators can be reduced to latent indicators that share a common variance that is unobservable, i.e., cannot be directly measured (Yong & Pearce, 2013, p. 80). However, certain limitations exist when using factor analysis. For instance, Yong and Pearce (2013, p. 81) observed that factor naming could be problematic and several variables may exhibit split loadings In addition, using pooled samples

[13] As outlined above, Castleman n(2011, p. 9) recommends using indicators that capture specific incidences such as humiliation and violence or using self-reported recognition levels.

with different time points may make factor scores unreliable and replication difficult. To combat these challenges and develop an index that measures human recognition, we suggest the Alkire-Foster method (Alkire & Foster, 2011, pp. 476–487), originally developed for multidimensional poverty counting.

Counting Multidimensional Human Recognition Deprivations

Alkire et al. (2013, p. 71) argue that deprivation indices should identify the people deprived as well as measure the extent of their deprivation. Thus, the Alkire-Foster method of multidimensional poverty counting (Alkire-Foster method) is presented here as a novel application of measuring human recognition deprivation. The adapted Alkire-Foster method allows one not only to identify the number of human recognition deprived people across social domains of interaction but also identify the intensity of said deprivation (Alkire & Foster, 2011, p. 477). Furthermore, it establishes two thresholds that are: (a) applied to indicators within domains of interest and (b) applied overall, to identify the number of domains in which an individual is considered deprived. Other useful properties are that it allows for decomposing across groups, ethnicity, and locality and it is based on Sen's (2005, pp. 155–161) capability approach and Atkinson's (2003, pp. 51–65) counting method for measuring deprivations.

Formally, the HRD Index is based on two components, the headcount ratio, H , and the deprivation intensity, A , as shown below (Alkire & Foster, 2011, p. 477):

$$HRDI = H \times A \tag{3.1}$$

Where

$$H\left(y;z\right) = \frac{q}{n} \tag{3.2}$$

and q refers to the total number of deprived individuals, divided by the total population, n.

The total number of deprived individuals, q, is given by:

$$q = q(y;z) = \sum_{i=1}^{n} \rho_k (y_i; z_j) \tag{3.3}$$

whereby q is identified by mapping the individual i achievement vector, $\rho_k (y_i; z_j)$, where y_i shows the individuals' $i = 1, 2, 3 \cdots, n$ achievement in j domains. Each domain $j = 1, 2, 3, \cdots, d$ is represented by a row of vectors showing domain-specific thresholds, z, with $z_j > 0$ where z_j is the first threshold below which individuals are classified as deprived in domain j. The identification parameter ρ_k identifies deprived individuals using their achievement vector, y_i, and the deprivation cut-off, k as shown below. Specifically, let the matrix of achievement $n \times d$ of individuals $i = 1, 2, 3 \cdots, n$ in the domains of interaction from $j = 1, 2, 3, \cdots, d$ be:

$$\begin{bmatrix} y_{ij} & \cdots & y_{nj} \\ \vdots & \ddots & \vdots \\ y_{id} & \cdots & y_{nd} \end{bmatrix} \geq 0. \tag{3.4}$$

The row vector y_i shows the individual's achievement while the column vector y_{*j} gives the distribution of the j domain achievement across individuals. The first threshold, z_j identifies individuals deprived in the domain j. The second threshold identifies the deprivation cut-off, *k*, by counting the number domains required for individuals to be considered deprived in multiple domains. When $k = 1$, the identification parameter, ρ_k , is equal to the union approach where deprivation is only in one domain. When $k = d$, the intersection approach is identified by ρ_k where individuals deprived in all domains are considered. The headcount ratio is adjusted by the deprivation intensity, A , to calculate the final index (Alkire & Foster, 2011, pp. 477–480) in equation (1). Deprivation intensity, A, is illustrated below as:

$$A = \frac{|c_i(k)|}{qd} \tag{3.5}$$

and describes the fraction of possible domains in which, on average, deprived individuals are deprived in (Alkire & Foster, 2011, pp. 476–479). The deprivation censored count, c_i, of individuals, *i*, is a dichotomous variable that takes the value of 1 when the deprivation score $c_i(k)$ is greater than or equal to the deprivation cut-off, k and 0 if otherwise. That is:

$$\rho_k\left(y_i; z_j\right) = 1 \text{ when } c_i \geq k \text{ and } \rho_k\left(y_i; z_j\right) = 0 \text{ when } c_i < k \tag{3.6}$$

Identification and Measurement

Assuming that an identification parameter ρ_k, has been selected, the ability to determine the HRDI is to ascertain first, the percentage of the sample population that is deprived using the headcount ratio, H and second by adjusting the headcount ratio, H with the intensity of deprivation, A. Thus, the HRDI is given as

$$HRDI = H \times A = \left(\frac{q}{n}\right) \times A \equiv \left(\frac{\sum_{i=1}^{n} w_i \rho_k (y_i, z_j)}{n}\right) \times \left(\frac{w_i \left|c_i(k)\right|}{qd}\right) \tag{3.7}$$

The HRDI is a member of multidimensional measures associated with Foster, Greer, and Thorbecke (1984, pp. 761–766) and is sensitive to the frequency and intensity of deprivations. It also satisfies various properties[14] including weak dimensional monotonicity and decomposability across groups (Alkire & Foster, 2011, p. 478). Defining the HRDI on averages implicitly assigns equal weighting, $w_i = \dfrac{1}{j \cdots d}$ to each domain, j, where $j \cdots d$ is the total number of domains assessed. Alkire and Foster (2011, pp. 477–480) argue this is ideal if all domains have equal impact. In addition, using

[14] For more on the derivations of the adjusted headcount ratio and its properties, see Alkire and Foster (2011, pp. 478–482).

general weights for the domains should also be open to debate and scrutiny. However, other weighing methods exist where domain weights could be nested[15].

Empirical Specification for Multidimensional Human Recognition Deprivation

Equation (7) can be written as a composite index of aggregate human recognition, $\bar{r}_i$:

$$\bar{r} \equiv HRDI = H \times A = \left(\frac{q}{n}\right) \times A \equiv \left(\frac{\sum_{i=1}^{n} w_i \rho_k(y_i, z_j)}{n}\right) \times \left(\frac{w_i \left|c_i(k)\right|}{qd}\right) \tag{3.8}$$

Where $\sum_{i=1}^{n} w_i \rho_k(y_i, z_j)$ is the weighted sum of individuals identified as deprived and $w_i \left|c_i(k)\right|$ denotes the weighted sum of possible recognition deprivation accruing to deprived individuals, *i*.

Data

Our empirical application is illustrated using pooled cross-sectional DHS data from Malawi for 2004, 2010, and 2015 (USAID, 2017b). Malawi is a landlocked country in sub-Saharan Africa with agriculture as the backbone of its economy. In 2006, agriculture contributed about 80% to export earnings and employed 85% of its workforce (World Bank, 2018a). High rates of poverty are prevalent in the country with a poverty ratio (% of population) of over 50% at the national poverty line and over 70% of the population living below $1.90 a day for 2004 and 2010 (World Bank, 2018a). Malawi's Multidimensional Poverty Index (MPI)[16], a measure of acute poverty, was 38.1% and

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[15] See Alkire and Foster (2011, pp. 482–483) for a detailed breakdown on the derivation of the nested weighting structure.

[16] The MPI is as a measure of acute poverty and is calculated by the United Nations Development Program (UNDP). It is calculated for three dimensions of poverty namely health, education and living standard. Each dimension is based on several indicators: health relates to two indicators, namely malnourishment and child mortality. Education is reflected by another two 2 indicators, years of schooling and school attendance. The living standard comprises six indicators: cooking fuel,

33.4% with average poverty intensities at 52.8% and 50.1% for 2004 and 2010 respectively (Alkire & Santos, 2014, pp. 251–274). Women make up about 52% of the total population and about 70% of these women are employed in agriculture (World Bank, 2018a). As we have highlighted the link between human recognition deprivation and poverty, we also briefly compare the similarity between the deprivation intensities of overall multidimensional poverty and human recognition deprivation for women in Malawi.

Choice of Domains, Indicators, Weights and Cut-off

We cluster indicators of violence, humiliation, dehumanization and autonomy with regards to their sources within three domains, namely the self[17], household, and community domains as summarized in Table 3-1 below. The indicators of human recognition show the occurrence of specific actions/perceptions in human recognition transactions. The rationale for using these variables are outlined by Castleman (2012, pp. 35–36). Humiliation and emotional violence are the variables closest to measuring recognition transactions because humiliation involves the degrading and devaluing a person as a human being. Physical forms of violence and sexual violence are examples of high manifestation of negative human recognition because perpetrators of said violence usually does not view their victims as humans but as objects or property and treat them as such. Women's justification of violence towards themselves and women's right to freedom and self-determination are also included. The former signals to what extent the woman views herself as deserving abuse while the latter clearly signifies to what extent the autonomy and basic rights of women are valued (Castleman, 2012, p. 36).

sanitation, water, electricity, floor, and assets, see Alkire and Santos (2014, pp. 251–274) for more details.

[17] Because human recognition transactions are bidirectional requiring provision and reception of recognition, we identify the self-domain with self-perception of violence to one's self to capture distinct interactions of recognition provision, to oneself, i.e., mental acceptance of violence and autonomy on decisions pertaining to one's self.

Using the indicators as shown in Table 3-1, we estimate the HRD index for Malawi. The indicator variables are binary, and the domains were ordered as follows:

Self-domain: If the woman has any degree of autonomy in decisions pertaining to (a) her health, (b) interactions with her family and (c) her household. The woman's justification of received/expected violence from individuals within the household and the woman's interaction with individuals in the household in terms of freedom.

Household domain: If the woman has any degree of freedom within her household. If the woman has experienced physical, mental, emotional or sexual violence and injuries within the household.

Community/institutional domain: If the woman has experienced physical, mental, emotional or sexual violence normally or during pregnancy within her community.

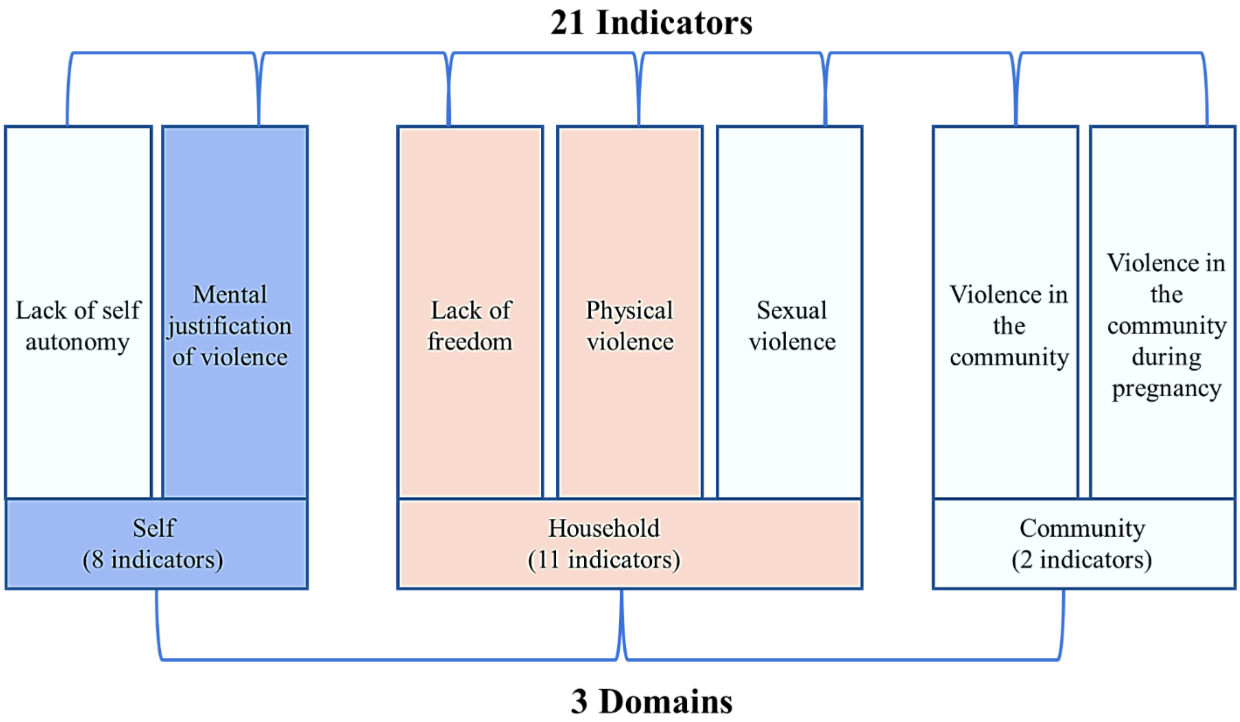
Table 3-1 Domains of human recognition and indicators

Domain	Source of human recognition	Domain indicators
Self (1)	Lack of self autonomy.	Person with …
		- usually decides on respondent's health care.
		- usually decides on visits to respondent's family/relatives.
		- usually decides on household purchases.
	Mental justification of violence.	Beating justified if … - wife goes out without telling spouse/partner
		- wife neglects children
		- wife goes argues with spouse/partner
		- wife refuses to have sex with spouse/partner
		- wife burns food
Household (2)	Interaction within the household regarding of freedom.	Spouse/partner … - jealous if respondent talks with other men
		- accuses respondent of unfaithfulness
		- doesn't permit respondent to meet with female friends
		- tries to limit respondent's contact with family
		- insists on knowing where respondent is
	Incidence of physical and sexual violence.	Respondent has been … - humiliated, threatened with harm, insulted or made to feel bad by spouse/partner.
		- pushed, shook, had something thrown at, slapped, punched with a fist or hit by something harmful, had arm twisted or hair pulled by spouse/partner.
		- kicked or dragged, strangled or burnt, threatened with knife/gun or another weapon by spouse/partner.

		- physically forced into an unwanted sexual act or forced into another unwanted sexual act by spouse/partner.
		- physically forced to perform sexual acts respondent didn't want to.
		- received bruises, eye injuries, sprains, dislocations or burns because of spouse/partner actions
		- hurt spouse/partner during a pregnancy.
Community (3)	Incidence of physical and sexual violence within the community.	Someone else … - physically hurt respondent in the community. - hurt respondent during pregnancy in the community.
Notes: Indicators derived from the Malawi DHS.		

In setting the cross-domain cut-off, k , Alkire and Foster (2011, pp. 482–483) argue that a cut-off choice could be a normative. Thus, the identification parameter, ρ_k , which is derived from the across-domain thresholds, k , depends on attributes that are included in the domain. For deprivation in domains that can result in gross human rights violation, one could allow across dimension cut-off, k , to be set to the minimum (union) to show that all human rights are essential and have equal status. Similarly, Alkire et al. (2013, pp. 76–78) show women's inadequacy in one domain may affect their wellbeing overall. Thus, we argue that deficiency in one domain is sufficient to identify women who are recognition deprived, thus, set the cut-off point, k , to 33% (Alkire & Foster, 2011, pp. 482–483) for our analysis of women working in agriculture. We report three values for k *:* the multidimensional identification where k =33% or 66% and intersection identification where k =100%. When k = 33%, a person must be deprived in at least, 33% of the weighted indicators in order to be considered deprived. That equals, at least, all the indicators in one of the three domains or, for example, a combination of four self-indicators, six household indicators plus one community indicator. Consider a woman living in Malawi with human recognition deprivation in the highlighted indicators for the self and household domains as illustrated in Figure 3-1 below.

Figure 3-1 Domains and indicators of multidimensional human recognition deprivation



Source: Author's presentation

To identify if the woman, in this particular case, is human recognition deprived, we sum up the weighted indicators as 0.04 x 4 indicators (self-domain) + 0.03 x 8 indicators (household domain) = 0.24 + 0.16 = 0.4, i.e., 40%. We see that indeed; this woman is deprived in over 33% of the indicators and is, thus, human recognition deprived in multiple dimensions.

Results

Deprivation Headcount Ratio, the Deprivation Intensity, and the HRD Index

We examine the following measures: (a) the deprivation headcount ratio (*H*), the deprivation intensity (*A*), and the HRD Index; (b) the decomposition by three regions of Malawi and women working in agriculture. Table 3-2 presents the three measures. The domain cut-off identifies women who are deprived in at least, one domain (k =33%), two domains (k =66%) or all three domains (k =100%). The deprivation headcount ratio (H) shows that about 16.4% of women in Malawi are deprived in one domain while 0.6% are deprived in two domains with deprivation intensities of 43% and 67%, respectively.

Table 3-2 Deprivation headcount ratio, the deprivation intensity, and the HRD Index of women in Malawi

	k=33%	*k*=66%	*k*=100%
Deprivation headcount ratio	0.164 (0.004)	0.006 (0.001)	0.000 (-)
Deprivation intensity	0.433	0.667	-
HRDI	0.071 (0.002)	0.004 (0.001)	0.000 (-)

Notes: Observations =19,282; Standard errors in parentheses; HRDI= Human recognition deprivation index; Values rounded to 3 decimal places.

We compare the multidimensional poverty index to the HRDI of Malawi as shown in Table 3-3. Although there are clear differences in index values, the intensity of deprivation for each index range between 43-49% for the years analyzed.

Table 3-3 Comparing multidimensional poverty and human recognition deprivation in Malawi

	Poverty *(k=33%)*	*Human recognition deprivation* (*k*=33%)
Headcount ratio	0.621	0.164
Intensity	0.493	0.433
Poverty/deprivation index	*Multidimensional poverty* *(MPI)* 0.308	*Human recognition deprivation* *(HRDI)* 0.071
Observations	n.a.	19,282

Notes: Years observed =2004, 2010, 2015/16; HRDI= Human recognition deprivation index; For the Multidimensional poverty index (MPI), values were calculated at household level while Human recognition deprivation (HRDI) values are calculated at the individual level for women only. For more on the MPI, see Alkire and Santos (2014, pp. 251–274).

An interesting question arises on whether results change if different k cut-offs and weights are assigned to the three domains. Particularly, how will the HRDI change if increasing emphasis is placed on one domain. We present the deprivation headcount ratio, deprivation intensity, and HRDI with several relative weights, which place emphasis on two salient domains: the self-domain and household domain. This allows us to check the robustness of our values close to the selected cut-off of 33%. Table 3-4 and Table 3-5 below presents the results of the measures with the self-domain and household domain indicators set to a relative weight of 1.5 (50%) respectively. Particularly in Table 3-4, we increase the weight on the self-domain such that it contributes 50% to the HRDI while we limit the household and community domains contributions to 25% each. Similarly, Table 3-5, we increase the weight on the household domain such that it contributes 50% to the HRDI while we limit the self and community domains contributions to 25% each.

As expected, the new weighting structure impacts the interpretation of cut-off, k , in both tables with the union identification at lowest k =25% and two relevant intermediate cases. When k =50%, every person identified as deprived is lacking in either the self-domain or in both the household and community domains (Table 3-4). Interestingly, the deprivation headcount ratio is 0.049 and the HRDI is 0.028. However, deprivation intensity rises to 58%. That is ca. 5% deprived individuals are deprived in 58% of the indicators.

When contrasted with table 5 at *k*=50%, we see that the deprivation headcount ratio is 0.04 and the HRDI 0.025. Similarly, deprivation intensity increases to 60%, indicating that 4% of identified deprived individuals are deprived in 60% of the indicators.

Table 3-4 Human recognition deprivation for women in Malawi: Self-domain with general weights

	k=25%	*k*=50%	*k*=75%	*k*=100%
Deprivation headcount ratio	0.443 (0.005)	0.049 (0.002)	0.001 (0.000)	0.000 (-)
Deprivation intensity	0.357	0.577	0.800	-
HRDI	0.158 (0.002)	0.028 (0.001)	0.001 (0.000)	0.000 (-)

Notes: Weights for the self-domain indicators: w1=1.5 (50%); w2=w3=0.75 (25%); Observations =19,282; Standard errors in parentheses; HRDI= Human recognition deprivation index; Values rounded to 3 decimal places.

Table 3-5 Human recognition deprivation for women in Malawi: The household-domain with general weights

	k=25%	*k*=50%	*k*=75%	*k*=100%
Deprivation headcount ratio	0.327 (0.005)	0.042 (0.002)	0.002 (0.001)	0.000 (.)
Deprivation intensity	0.373	0.597	0.800	-
HRDI	0.122 (0.002)	0.025 (0.001)	0.002 (0.000)	0.000 (.)

Notes: Weights for the household-domain indicators: w2=1.5 (50%); w1=w3=0.75 (25%); Observations =19,282; Standard errors in parentheses; HRDI= Human recognition deprivation index; Values rounded to 3 decimal places.

Note, from Table 3-4 and Table 3-5, that deprivation intensity is higher for indicators in the household domain than for the individual domain and converges at k =75% indicating that the intensity of human recognition deprivation increases rather on human recognition transactions occurring at the household level than on the individual level. In other words, the breath of deprivation at the household domain is high compared to the individual domain for women in Malawi.

Decomposition by Region and Occupation

Once the deprived have been identified, one of the key properties of the HRDI according to Alkire et al. (2013, p. 77) is that results can be decomposed to reveal contributions of groups[18]. The rationale for decomposability is that the contribution from a group may exceed its population share and thus bears a disproportionate share of deprivation (Alkire et al., 2013, p. 78). Table 3-6 below decomposes the HRDI by the three regions in Malawi. Here, we focus only on the cut-off, k *=33%*. The deprivation headcount ratio indicates higher human recognition deprivation for women in northern Malawi compared to women other regions.

Table 3-6 Decomposing deprivation measures by region, in Malawi

Region	Measures	*k*=33%	*k*=66%	*k*=100%
Northern Region	Deprivation headcount ratio	**0.204**	**0.007**	0.000
	Deprivation intensity	0.441	0.714	-
	HRDI	0.090	0.005	0.000
Central Region	Deprivation headcount ratio	**0.175**	**0.006**	0.000
	Deprivation intensity	0.410	0.833	-
	HRDI	0.076	0.005	0.000
Southern Region	Deprivation headcount ratio	**0.146**	**0.004**	0.000
	Deprivation intensity	0.401	0.750	-
	HRDI	0.063	0.003	0.000

Notes: Observations =19,282; Contribution of subgroups to indices (%); HRDI= Human recognition deprivation index; Values rounded to 3 decimal places.

We further decompose the HRDI by women working in agriculture and outside agriculture. Table 3-7 below presents the results for all three cut-off points. At the minimum (k =33%), 17.5% of women working in agriculture are deprived with a deprivation intensity (A) of 43% across all weighted indicators compared to 15.6% for women not employed in agriculture.

[18] For a detailed breakdown on the notations used for decomposing the index by groups, see Alkire and Foster (2011, pp. 476–487) and Alkire et al. (2013, pp. 71–91).

Table 3-7 Decomposing deprivation measures by women in Malawi working outside agriculture and in agriculture

Occupation	Measures	k=33%	k=66%	k=100%
Outside Agriculture	Deprivation headcount ratio	0.156	0.005	0.000
	Deprivation intensity	0.436	0.833	-
	HRDI	0.068	0.004	0.000
Agriculture	Deprivation headcount ratio	0.175	0.006	0.000
	Deprivation intensity	0.434	0.667	-
	HRDI	0.076	0.004	0.000

Notes: Observations =19,282; Contribution of subgroups to indices (%); HRDI= Human recognition deprivation index; Values rounded to 3 decimal places.

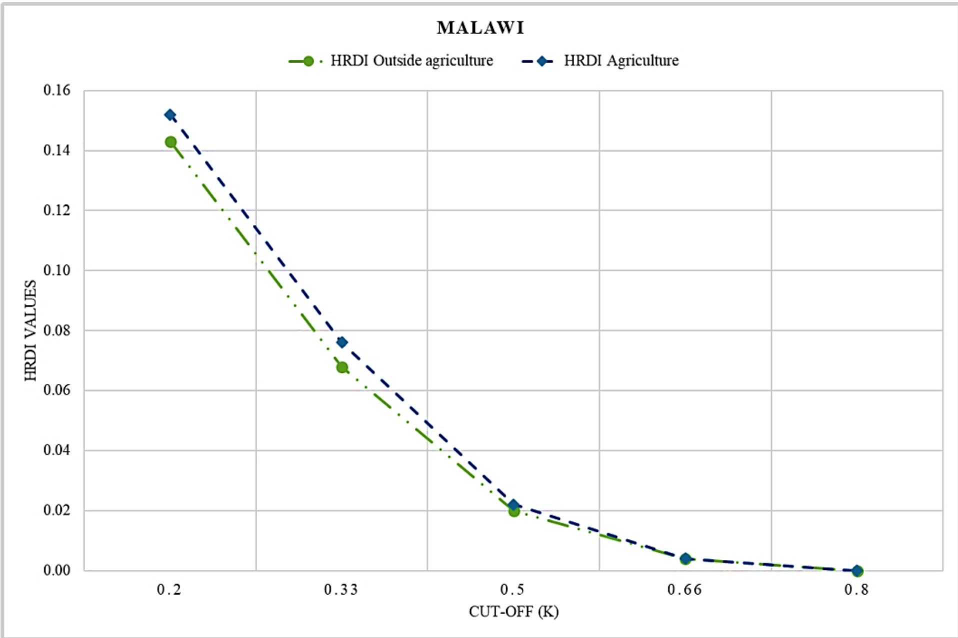
Overall, 16.4% of women identified as deprived in Malawi have, on average, inadequate recognition in 43% of the weighted indicators. 17.5% of women working in agriculture are deprived with an intensity of 43%.

Robustness Tests

Ranking and dominance of cut-off

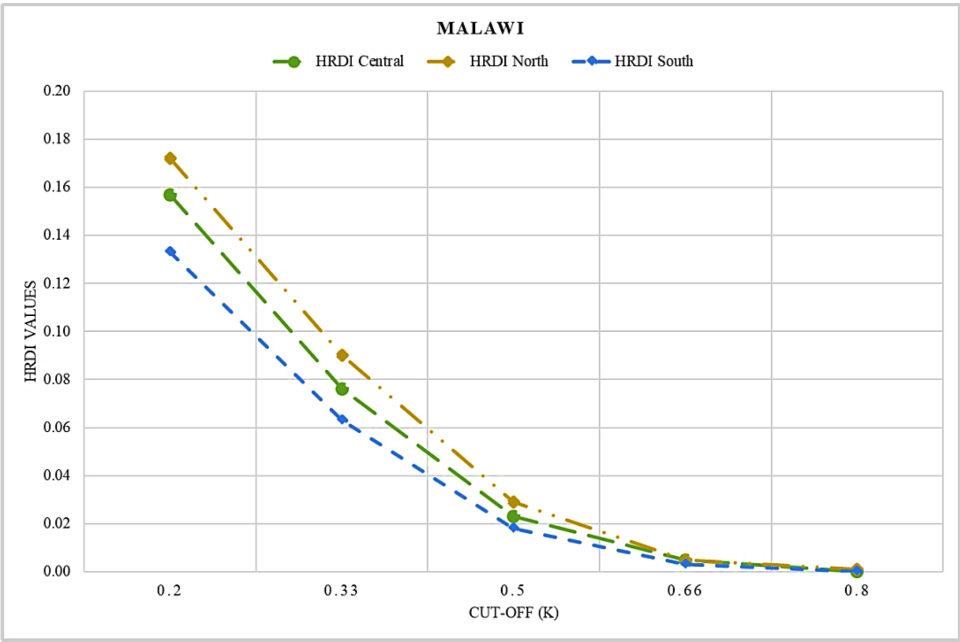
In line with Alkire and Foster (2011, pp. 482–483), we check the robustness of our choice of cut-offs by checking for first-order stochastic dominance and rank robustness of overall cut-offs, occupational group as well as spatial dominance of regional splits. It involves testing whether there is robust ranking of human recognition deprivation between regions. That is if a group as shown in the regional splits or agricultural occupation splits ranked monotonously with changes in cut-offs from k =0.2(20%) …. 0.8(80%). The HRDI shows that the cut-offs for the domains (see HRDI in Table 3-4 and Table 3-5), the ranking of the occupational groups (see Figure 3-2) and regions (see Figure 3-3) are robust and dominant. We refer to Alkire and Foster (2011, pp. 482–483) for the proof of first-order and second-order stochastic dominance of a multidimensional index.

Figure 3-2 HRDI rank dominance for women working outside agriculture and in agriculture



Note: HDRI = Human recognition deprivation index

Figure 3-3 HRDI rank dominance for regions



Note: HDRI = Human recognition deprivation index

Discussion

Human recognition in our study was captured by applying a unique method for measuring intangible components of poverty. The applicability of the Alkire and Foster (2011, pp. 476–487) method from traditional poverty measurement to the sphere of interpersonal space and relationships created a novel approach in which abstract concepts of human development can be concretized and measured. Selection of the indicators, weighing and domain cut-offs present a picture that not only encloses the concept of human recognition within socio-cultural, political and economic context of development but argues for consistency across the framework of universal human rights – rights to be free from harm, violence and the right to be recognized. Furthermore, the multidimensionality of the HRD Index also supports the argument of Malhotra and Schuler (2005, pp. 73–77), namely that the problem of gender inequality spreads and varies across social, economic and psychological domains.

The empirical illustration of the Alkire-Foster method using Malawi's DHS data reveals human recognition deprivation in the domains of interaction as highlighted by Castleman (2016, pp. 135–151). Our results show that the methodology can identify human recognition deprived individuals with robust properties. Assigning general weights to our domains shows women experience higher human recognition deprivation within the household as theorized by Choi and Ting (2008, p. 849), Hayes and van Baak (2016, 1365) and Fidan and Bui (2016, pp. 1077–1078) for power dynamics in the household.

Decomposing by the three regions within Malawi shows that manifestation of human recognition deprivations can vary across regions. For example, in Malawi, the deprivation headcount shows that women in the northern region of Malawi display the highest share of deprived women. One could attribute this to the patrilineal structure of the north which confers less freedom, autonomy and power on women as opposed to matrilineal structure in the central and south (Conroy, 2014, p. 869). Disaggregating the HRD Index by employment also show that human recognition deprivation varies by agricultural employment for women in Malawi, for example.

Our application of the methodology and findings show interesting policy implications. According to Alkire and Foster (2011, p. 483), the various values of cut-offs, k could be used to highlight policy priorities and goals. For instance, assigning different weights to the individual and household domain shows higher human recognition deprivation intensity in the household domain in Malawi. Thus, policies for human recognition transactions in the household like gender violence awareness and laws protecting injured victims of physical abuse could improve human recognition transactions for women. Alternatively, policy makers could focus on multidimensionally deprived strata of the population by setting cut-off points higher or lower to investigate a smaller or a larger group with joint deprivations as illustrated for regional and agricultural decomposition. The choice of the cut-off point can also be used to highlight and target women suffering the highest intensities of human recognition deprivations as illustrated for women in agriculture. Slicing out a sub-population could allow analysis on policy sections like resource access, to be carried out which, otherwise, would have been expensive or impossible due to program budget constraints. Finally, this methodology can be applied to measure other intangible concepts of development in Malawi as well as in other countries.

Concluding Remarks

We propose an index of multidimensional Human Recognition Deprivation (HRD) that measures to what extent individuals (women) are viewed and valued as human beings as well as treated given this value. The design of the Index draws on the framework of Sen's capability approach and highlights how human recognition deprivation can be an attack on one's freedom. Finally, we develop an aggregate measure of human recognition deprivation applying the Alkire-Foster method on indicators of humiliation, dehumanization, violence and lack of autonomy for women within the self, household and community domains. Using Malawi DHS from 2004, 2010 and 2015, we calculate the multidimensional HRD Index, deprivation intensity and deprivation head count ratio.

We found that women in Malawi are recognition deprived with deprivation intensities varying across regions and occupation (working in agriculture). Our intensity of human recognition deprivation also shows interesting similarities in breath with the intensity of poverty in Malawi overall.

Our overall study presents relevant implications for development policy that, which better captures the modelling of intangible factors of socio-economic development such as human recognition. Furthermore, the methodology could be applied in other countries as well where human recognition deprivation levels for women are still significant. By assigning different domain cut-offs and weights, policy makers could analyze, identify and target specific domains or sub-populations of individuals (women) with programs aiming at improving human recognition levels; impacting resource access and poverty. Finally, our study aims to contribute on the literature that investigates the measurement of intangible components of human development for future policies.

We are limited by the use of cross-sectional data in our analysis. We also note that it would be interesting to monitor the change of human recognition deprivation of women over time using panel data. This would, definitely, be a useful tool for policy makers in evaluating the efficacy of human recognition improvement interventions.

4. Identifying Human Recognition Deprived Women: Evidence From Malawi and Peru

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Abstract

Using data from the Demographic and Health Surveys from Malawi and Peru, we identify human recognition deprived women and analyse social-demographic and socioeconomic factors influencing human recognition deprivation. We find educated spouses/partners are less likely to provide negative human recognition to women. We also observe women's education has a small non-monotonic impact on the likelihood of human recognition deprivation. Women are also likely to be deprived if they were married more than once, have alcoholic partner/spouses and exert retaliatory behaviour. Additional heterogeneous outcomes exist for agricultural women in both countries. We argue that women's human recognition can be improved overall with social policies/programs tackling alcohol use, violence and education in both countries.

Keywords: agriculture, women, human recognition, poverty, violence, Malawi, Peru

JEL codes: D01 D63 O13 I31 I32 Q01 Q10 J16

Introduction

Kabeer (1999, p. 437) argues that poverty[19] in developing agrarian-based societies influences how women are valued and treated. Poverty is embedded in societies by its connection to the social systems and systemic disregard for certain groups of persons in the population like women (Schweiger, 2015, p. 147). Schweiger (2015, p. 146) interprets poverty as recognition deprivation because under poverty, social relation experiences are constrained. So, poverty affects human recognition through its effect on power and choice. Drawing on the Hegelian[20] theory of recognition, Laitinen and Ikäheimo (2011, p. 5) identify the concept of recognition[21] as core to psychological, social and institutional interactions in human society. Similarly, Castleman (2013, p. 1, 2016, p. 135) defines human recognition as "[…] the acknowledgement provided to an individual by other individuals, groups, or organizations that the individual is of inherent value with intrinsic qualities in common with the recognizer, i.e. recognition as a fellow human being […]". Furthermore, Castleman (2016, p. 135) outlines that human recognition transactions can be identified by individuals' treatment of others, usually in a "bidirectional relationship" [22].

Linking economic behaviour to receipt of recognition from others, lack of positive interactions including acknowledgement, respect, status, power, love and sociability, shows startling effects on the wellbeing of deprived individuals (Castleman, 2013, p. 1). Human recognition is interwoven with

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[19] Poverty here refers to monetary and non-monetary lack of means and includes recognition deprivation.

[20] See Hegel (1991) and Hegel and Miller (1977).

[21] According to Laitinen and Ikäheimo (2011, p. 5), when individuals are recognized, they are able to build and maintain healthy personalities and improve the qualities of their social and economic life. Laitinen and Ikäheimo (2011, p. 5) understood the concept of recognition to involve identifying and acknowledging "an entity to be of value" plus further applying these sub-concepts to only persons, groups of persons in the interpersonal sense. This is in line with Castleman's (2013, p. 8) definition of human recognition.

[22] See Castleman (2016, p. 135), for details on the theory of human recognition and its role in development.

other missing dimensions of poverty[23] (Castleman, 2013, p. 6) and arguably plays constitutive and instrumental roles[24] on human development (Castleman, 2013, p. 1). For women, the manifestation of negative recognition is often portrayed in forms of violence and dehumanization because of unequal bargaining power. Poverty links to human recognition through its components like self-/social-esteem[25],freedom, power and choice. Consequently, depriving individuals of recognition reinforces disempowerment, which increases poverty. In agrarian societies in sub-Saharan Africa, human recognition transactions in the community (institutional), interpersonal (household), and the intrapersonal (self) domains can be influenced by several factors. Particularly, social norms, gender and social capital can shape community institutions, considerably influencing how much recognition women receive. Theoretical and empirical evidence suggests that social-demographic and socioeconomic factors that improve women's value, empowerment and regard within the society may be used to identify women with higher human recognition. For instance, Grabe, Grose, and Dutt (2015, p. 15) note that women with complete autonomy over their land resources enjoy elevated status, respect and recognition within their communities. Likewise, Vyas and Watts (2009, p. 577), Emran, Maret-Rakotondrazaka, and Smith (Alkire, pp. 347–359; 2013, p. 481), Mocan and Cannonier (2012, p. 17) and Flake (2005, p. 364) observe that women's education significantly and positively improves their autonomy, freedom of choice and monetary empowerment. Thus, understanding factors supporting human recognition deprivation is necessary to identify deprived people in order to provide targeted measures to improve their livelihoods.

We analyse the external factors influencing human recognition deprivation for women in Malawi and Peru. Our analysis is illustrated using the pooled cross-sectional Demographic and Health Survey

[23] See Alkire (2007, pp. 347–359) for an introduction into the missing dimensions of poverty.

[24] See Sen (2001) for constitutive and instrumental roles of intangible components of development. Human recognition is significant in itself for human development and instrumental in supporting an individual's opportunities towards valuable outcomes Castleman (2013, p. 8).

[25] Social-/self-esteem is defined from the viewpoint of injustice and freedom by Schweiger (2015, p. 144) as the notion that everyone deserves to be recognized for their contribution to society.

(DHS) datasets for Malawi and Peru. We hypothesize that several social-demographic and socioeconomic factors directly or indirectly increase/decrease the likelihood of experiencing human recognition deprivation. We acknowledge country-specific variations but argue that certain factors can be identified across countries, which are specific to women, with direct impact on their wellbeing.

We contribute to the research on human recognition related to social-demographic and socioeconomic (human) development of women in both countries in the following respects. First, using the Alkire-Foster method, we highlight the depth and breadth of human recognition deprivation for women in both countries, identifying women who are deprived in one and more than one domain. We also present how human recognition deprivation varies for women in agricultural and non-agricultural occupations. Second, we show that indeed, several socioeconomic and social demographic factors significantly influence human recognition deprivation and observe its heterogenous effects across both countries.

It is possible that our analysis could be exposed to bias from endogeneity in our social-demographic and socioeconomic indicators. As we do not include any instrumental variable regressions, we interpret our findings as correlates of human recognition deprivation. Going forward, we establish a conceptual framework for human recognition deprivation, describe our overall methodology, report and discuss our results, conclude and give policy recommendations.

Conceptual Framework for Estimating Human Recognition Deprivation

Interpersonal, Community Violence and Human Recognition

The manifestations of negative human recognition encompass formal and informal forms of impediments. Violence is a particular despicable form of negative human recognition; which women experience as a class. Violence in this regard refers to violence in all forms from direct/interpersonal[26]

[26] Direct/interpersonal violence includes physical, sexual, emotional and psychological violence.

violence (visible violence) to cultural and institutional[27] violence (structural [28]/invisible violence) (Dilts, 2012, p. 191; Winter, 2012, pp. 195–196).

Complex dynamic social interactions of power explain threats to women's safety in general (Grabe et al., 2015, p. 8). Unequal power relations operate simultaneously at different social domains, like the community (institutional), interpersonal (household), and intrapersonal (self) domains, intersecting with human recognition transactions and informing our domains[29] of deprivation. Violence embedded in institutional structures[30] such as patriarchy shape how women wield power and are valued. As observed by Buchenrieder, Dufhues, Theesfeld, and Nuchanata (2017, p. 16), institutions shaped by culture[31] encompass endogenous practices which influence human interaction and persist over time. Thus, cultural practices which precipitate institutions like patriarchy inflict violence over time by justifying direct violence (visible) and legitimizing institutional violence

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[27] Institutions are defined as the formal and informal constraints that facilitate co-ordination among people, functioning as constraints that shape human interaction Alesina and Giuliano (2015, p. 902).

[28] Anglin (1998, p. 145) identifies structural violence as "[…] the expropriation of vital economic and non-material resources and the operation of systems of social categorization that subvert people's chances for survival [...]" and normalization of these practices as status quo. Gender relations fall into this category as women are not only socially and culturally marginalized but are denied the opportunity for emotional and physical wellbeing, exposing them to assault, rape and events that cause death. Also see Galtung (1969, pp. 167–191).

[29] We observe human recognition transactions across self (intrapersonal), household (interpersonal) and community (institutional) domains. See Castleman (2013, p. 1) for insight on domains of human recognition.

[30] According to Connell ((2012, p. 1677)), structures refer to large-scale patterns and cultural reference areas of everyday life with emotional and material constraints that occur across institutions, social and cultural sites including families and communities. Institutions here refer to community structures because in most agrarian communities, resource access, power and recognition are re-shaped at the cultural level and imbedded into institutions in the community.

[31] We define culture in line with Alesina and Giuliano (2015, p. 902) not as an informal institution but as a concept with equal footing with formal institutions (i.e., the law). For consistency, we restrict our use of these terms to institutions and culture/cultural practices.

(invisible). The intersection of direct, cultural and structural violence in women's social domains influences, among others, human recognition deprivation.

Direct/interpersonal violence as form of negative human recognition exists worldwide (Godden, 2013, p. 253; Wilson, 2013, p. 3). For instance, about 20-50 % of women worldwide have experienced violence, including the denial of basic needs, healthcare, and/or employment (Wilson, 2013, p. 4). Institutional violence affects women as a class and is most prevalent in women's control of resources, lack of autonomy and recognition, for example, as agricultural producers. Indeed, for developing countries whose economies still depend heavily on agriculture for employment, this situation poses an obstacle to food security, because women often cultivate food crops for subsistence consumption. Lack of recognition for women at the institutional level is also visible in the gender gap in agricultural productivity through differences in resource access (Palacios-López and López, 2015, p. 1175, overlooked land rights (Samanta, 2016, p. 242), and declining rural women's livelihood (Velayudhan, 2012, p. 505). Although, Grabe et al. (2015, p. 8) note positive linkages between women land ownership, power and reduced violence in Tanzania and Nicaragua, Bhaumik, Dimova, and Gang (2016, p. 242) find land ownership alone does not improve women's welfare in Malawi, for example, if appropriate inputs and supporting institutions do not exist. Vyas and Watts (2009, p. 577) observe an increasing risk of violence if women are employed but a decreasing risk if women attain higher education.

Factors affecting women's vulnerability to disempowerment, institutional and partner violence has been researched extensively (Flake, 2005, pp. 353–373; Issahaku, 2017, 1-14; Mkandawire-Valhmu et al., 2016, 1-26; Rondon, 2003, pp. 157–163; Wilson, 2013, pp. 6–7); (Doss, Kovarik, Peterman, Quisumbing, & van den Bold, 2015, pp. 421–423).

However, there is little literature linking social-demographic and socioeconomic factors to negative human recognition manifested as humiliation, dehumanization, violence[32] and lack of autonomy for

[32] Diprose ((2007, p. 438)) gives a definition on the role of interpersonal violence in multidimensional poverty calculation. In our analysis, institutional violence is represented as societal power inequality.

women in developing countries. To the best of our knowledge, this is the first empirical analysis that identifies individuals (i.e., women) who are human recognition deprived and explores the associations between social-demographic, socioeconomic factors and negative human recognition. We apply Castleman's (2013, p. 1, 2016, pp. 135–151) theory of human recognition and economic development in the following respects:

1) Using the Alkire-Foster method (Alkire & Foster, 2011, pp. 476–480), we calculate a multidimensional human recognition deprivation index (HRD Index) and establish the dichotomous censored count of deprived women (1 = deprived, 0 = otherwise).
2) Using the censored count, we explore the association between certain social-demographic and socioeconomic factors and human recognition deprivation clustered within three social domains, namely the self[33], household and community domains.
3) By carrying out a comparative study between Malawi and Peru, we ascertain to which extent our factors are consistent across both countries.

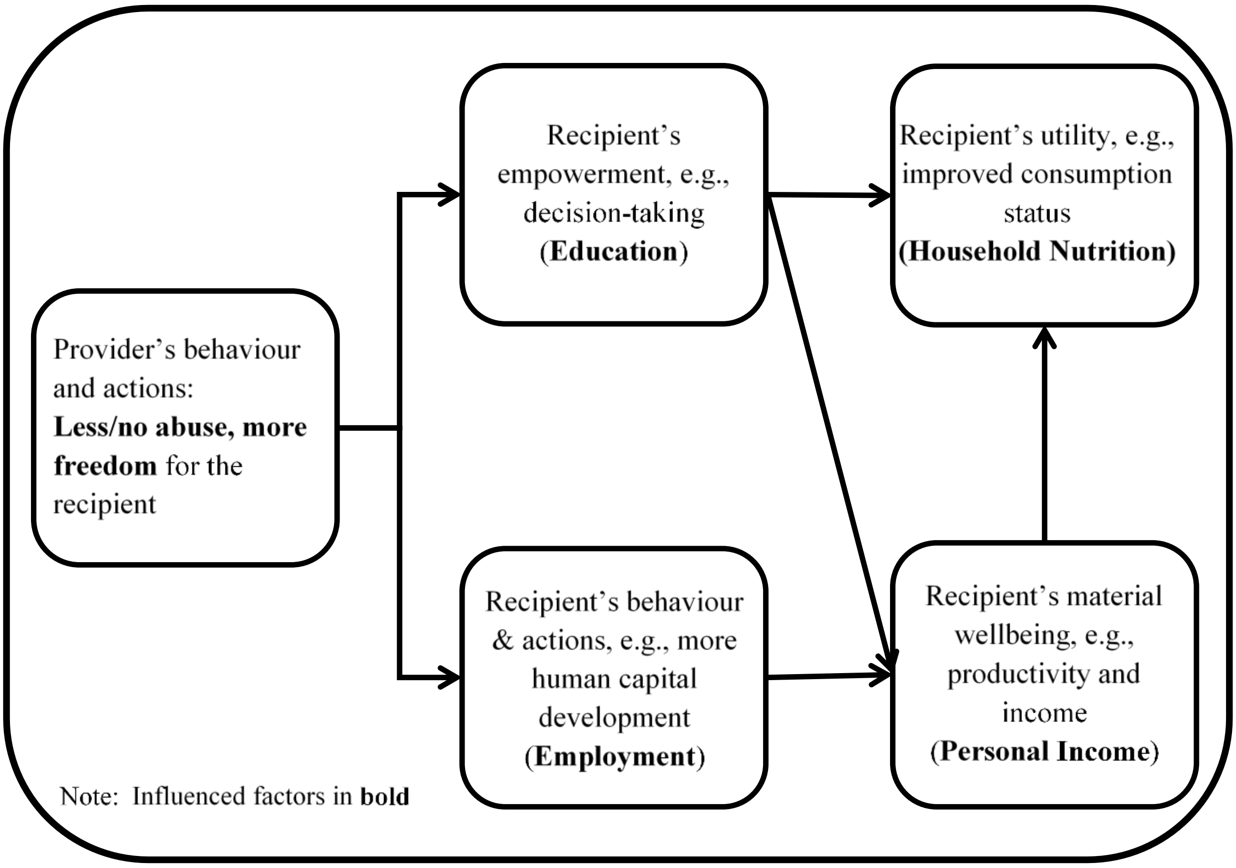
[33] Because human recognition transactions are bidirectional requiring provision and reception of recognition, we identify the self domain as capturing the distinct interactions of human recognition provision, to oneself in form of mental acceptance of violence; and decisions pertaining exclusively to oneself and one's environment. Particularly, self domain indicators capture the extent to which individuals' exercise final autonomy about personal concerns. These concerns are seen in decision making indicators on issues that affect ones' self like own healthcare, visit to one's family, among others. However, individuals 'ability to engage in decision making is determined by socio-cultural, religious, and ethnic setups that define gender roles. Generally, most studies find that poor and rural women are less likely to be involved in any decision making. For further details, see Acharya, Bell, Simkhada, van Teijlingen, and Regmi (2010, pp. 1–12), Alemayehu and Meskele (2017, pp. 213–221), Becker, Fonseca-Becker, and Schenck-Yglesias (2006, pp. 2313–2326) and Senarath and Gunawardena (2009, pp. 137–143).

A Methodological Framework for Estimating Human Recognition Deprivation

According to Castleman (2016, pp. 136–137), positive or negative human recognition exerts psychic and material effects[34] on its recipients. The amount of human recognition a person receives, depends on the extent to which his/her basic rights and needs "[…] are acknowledged to exist and to be of consequence […]" (Castleman, 2011, p. 3). Thus, if individual rights and needs are acknowledged and promoted, human development in the form of self-actualization begins. Self-actualization is achieved through the process of recognition (Honneth, 2001, p. 51), which depends on the preconditions acquired through cooperation and interaction with other fellow human beings. Consequently, human recognition can lead to changes in empowerment and dignity, which in turn affect the utility and material wellbeing of its recipients (see Figure 4-1 below). We argue that the impact of human recognition deprivation on women's wellbeing may be obscured if social-demographic and socioeconomic factors influencing recognition are not identified. Furthermore, targeted social policies/programs could address the low recognition status of women by modifying specific indicators influencing autonomy, violence and freedom.

[34] See Castleman (2013, p. 8); (2016, pp. 135–151) for detailed insights on the four distinct ways in which human recognition theoretically affects psychic and material wellbeing of its recipients.

Figure 4-1 Pathway of Human Recognition Impact



Source: Adapted and simplified from Castleman (2013, p. 8)

We apply the Alkire-Foster method to a set of negative human recognition indicators taking the framework in Figure 1 into account. The Alkire-Foster method establishes two thresholds, which are: (a) applied to indicators within our three domains of interest and (b) applied overall, to identify the number of domains in which an individual should be lacking in to be considered deprived.[35] The rationale for depicting the linkage between human recognition, humiliation, dehumanization, lack of autonomy and violence[36] is in line with Castleman (2011, p. 3)[37].

[35] See Alkire and Foster (2011, pp. 476–478) for a detailed explanation on poverty index derivation.
[36]See Alkire (2007, pp. 353–356) on physical safety and interpersonal violence as missing dimensions of poverty.
[37] According to Castleman (2011, p. 3), humiliation and emotional violence are closest measures of recognition transactions because they involve degrading and devaluing a person as a human being.

The estimation of the multidimensional **h**uman **r**ecognition **d**eprivation **i**ndex (hereon referred to as **HRDI**) is based on two components, the headcount ratio, H and the deprivation intensity measure, A. The head count ratio, H, is calculated by dividing the total number of deprived individuals by the total population while the deprivation intensity measure, A, is calculated as the fraction of possible domains in which average deprived individuals are deprived in. The deprivation censored count, c, is calculated as a dichotomous variable that takes the value of 1 when an individual's deprivation score is greater than or equal to the deprivation cut-off. The formulas are outlined in the Appendix.

Data and Estimation

Data Preparation for Malawi and Peru

Our empirical application is illustrated using pooled cross-sectional data from the Peru DHS for 2004-2012 and the Malawi DHS for 2004, 2010 and 2015 (USAID, 2017a, USAID, 2017b). The datasets contain information on the demographic and socioeconomic status of randomly selected respondents (women) aged 15-49. Since our human recognition deprivation indicators were selected from the Conflict Tactics Scale (CTS) module, only women who answered the conflict questions were included in the final analysis. Survey strata, weights and sampling units were set as provided in both datasets.

For this country selection, the following remarks apply. Malawi is a landlocked country in sub-Saharan Africa with an agrarian economy. Between 2004 and 2015, 81 % of the Malawian workforce employed in agriculture on average, were women (World Bank, 2018b). About 72 % of the population lives below US$ 1.90 a day with an average fertility rate of 5.3 births per woman (World Bank, 2018b). Peru is a country located in South America with 35 % of the population living in poverty and

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Physical forms of violence and sexual violence are examples of high manifestation of negative human recognition because perpetrator usually does not view victims as human but as objects or property. Women's right to freedom and self-determination are included because it signifies how women's autonomy and basic rights are recognized within the society.

fertility rates of 2.6 births per woman (World Bank, 2018b). Between 1960s and 1990s, agriculture was the main source of employment with total agricultural output at above 60 %.

For both countries, decline in agriculture is a threat to overall economic growth and food security (World Bank, 2018b). Yet, effective women participation in agriculture is constrained, given that impediments reduce their access to resources in combination with a lack of human recognition. Thus, comparing both countries is interesting because of their strong past and/or current reliance on agriculture as a traditional means of economic development. Furthermore, their geographical distances, cultural and socioeconomic diversity ensure that country-specific influences on human recognition deprivation are controlled for. This enables us to capture interesting estimates on the odds of human recognition deprivation for women. As hypothesized, we argue that certain social-demographic and socioeconomic factors in both countries, influence the likelihood of human recognition deprivation of women.

Human Recognition Indicators

We cluster indicators of violence, humiliation, dehumanization and autonomy with regards to their sources within three domains namely, self, household and community as summarized in Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-1. Measurement of human recognition deprivation, more precisely, domain-specific measurements are established based on the type of indicators included in the domains. For instance, if three weighted domains exist with five indicators measuring the presence of violence (0/1 to indicate absence/presence) in one of these weighted domains, the indicator cut-off will be set to one while the domain weight will be set to one-third (0.33). Individuals who indicated presence of violence in one of the indicators will be assigned a weighted score of $0.33/5 = 0.066$. Individuals with inadequate human recognition in all five indicators in this domain will accumulate a total weighted domain score of $0.066 * 5 = 0.33$. If across domain cut-off is set to 0.33, which identifies deprivation in one of the three domains (other domains are scored 0 in this example for simplicity), the individuals will be identified as deprived with a censored count of one as they are deprived in one of the weighted domains. Supported by Alkire et al. (2013, pp. 76–78) that women's inadequacy in one empowerment domain affect their wellbeing overall, we argue that deficiency in one domain is sufficient to identify women who are deprived, thus, setting our cut-off point, *k*, to 33%, see Section 2.2 (Alkire & Foster, 2011, pp. 482–483).

Analysis of Human Recognition Deprivation for Malawi and Peru

From our analysis, the deprivation headcount ratio, *H*, demonstrates that, overall, 16 and 19% of the women in Malawi and Peru are human recognition deprived with deprivation intensities at 43 and 45 % respectively. The proportion of weighted deprivation that women experience overall, HRDI, is 0.09 for Peru and 0.07 for Malawi (See Table 4-1).

Table 4-1 Multidimensional Human Recognition Deprivation Index, deprivation headcount ratio and deprivation intensity

k=33%	Overall		Agricultural women		Women outside agriculture	
	Malawi	Peru	Malawi	Peru	Malawi	Peru
Deprivation headcount ratio	0.164	0.194	0.175	0.200	0.156	0.185
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)
Deprivation intensity	0.431	0.458	0.433	0.462	0.436	0.454
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
HRD Index	0.071	0.089	0.076	0.093	0.068	0.084
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
% Observation			0.45	0.14	0.55	0.86
Observations	19,282	83,235	8,904	11,486	10,378	71,749

Notes: Agricultural women is a binary variable with value of 1 if woman works in agriculture (employee or self-employed) and 0 if otherwise. HRDI= Human Recognition Deprivation Index; Standard errors in parentheses

For women in agriculture, 17 and 20 % in Malawi and Peru are human recognition deprived with deprivation intensities of 43 and 46% respectively. Women in agriculture contribute are 45 and 14% to the overall HRDI in Malawi and Peru respectively. At a cut-off point (*k*) of 33%, self and household domains contribute the most to human recognition deprivation - from here on interchanged with recognition deprivation for simplicity- in Malawi and Peru respectively (see Figure **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-1). Interestingly, the self domain seems to contribute more to human recognition deprivation in Malawi than in Peru, highlighting the differences on how women view themselves in both countries. However, further research is needed to isolate how each self domain indicator contributes to overall human recognition in both countries.

In line with Alkire and Foster (2011, pp. 476–480), we check for robustness by investigating the effect of different cut-off points, *k*, at 20, 50, 66 and 80% (0.2, 0.5, 0.66 0.8) (See Figure **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-2) . The deprivation headcount ratio and HRDI show that the ranking of the two sub-groups are robust and yield dominance across both measures. Two sample T-test of differences in mean recognition deprivation scores between women outside agriculture (mean: Malawi = 0.300 (SD = 0.119); Peru = 0.238 (SD = 0.136)) and women in agriculture (mean: Malawi = 0.309 (SD = 0.118); Peru = 0.244 (SD= 0.141)) yielded -0.009 and -0.006 for Malawi and Peru respectively significant at 1% level, results are available on request) showing that women in agriculture in both countries display a higher mean recognition deprivation scores compared to their counterparts.

Logistic Regression Using Deprivation Censored Count

As previously outlined, we use a logistic regression model to estimate the likelihood of recognition deprivation associated with our set of independent, explanatory variables (see Figure A-1). As shown in Table 4-2 below, for both countries, we estimate the baseline likelihood of recognition deprivation (model 1) using the variables for agricultural occupation, age, education, household status and wealth index with time controls. Next, we expand the model specification to time interactions, social-demographic and socioeconomic interactions, and household characteristics (model 2) to explore the nonlinear pathways of impact over time. Finally, we present the full model controlling for country fixed effects (model 3).

Likelihood of Human Recognition Deprivation for Women in Malawi and Peru

Table 4-2 below presents the empirical evidence associating social-demographic and socioeconomic factors with recognition deprivation including country-specific variations. Columns (2), (3), and (4) present model 1, 2, and 3 estimates for Malawi while columns (5), (6), and (7) depict model 1, 2, and 3 estimates for Peru. For other analysis like percentage change in odds, summary statistics and marginal effects, please refer to the online supplementary materials. In the following, we present the percentage change in odds with the log odds in parenthesis for ease of interpretation.

Table 4-2 Log-likelihood of multidimensional human recognition deprivation in Malawi and Peru

	Malawi			**Peru**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Agriculture: Partner	0.081**	0.213**	0.139	-0.065**	-0.107	-0.086
	(0.038)	(0.099)	(0.100)	(0.030)	(0.083)	(0.085)
Agriculture: Woman	0.077**	0.171	0.196*	0.053*	-0.378***	-0.428***
	(0.036)	(0.111)	(0.113)	(0.030)	(0.146)	(0.150)
Head household: Woman	-0.317***	-0.364***	-0.323***	0.256***	0.147**	0.109
	(0.062)	(0.066)	(0.067)	(0.047)	(0.074)	(0.075)
Spouse/partner's age	0.002	0.000	-0.000	0.001	0.007*	0.008**
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
Woman's age	-0.019***	-0.021***	-0.021***	0.011***	-0.005	-0.005
	(0.004)	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)
Wealth index-poorest	0.111	-0.100	-0.130	0.253***	0.510***	0.554***
	(0.070)	(0.078)	(0.079)	(0.060)	(0.119)	(0.125)
-poorer	0.155**	-0.006	-0.016	0.531***	0.597***	0.550***
	(0.065)	(0.073)	(0.074)	(0.054)	(0.104)	(0.108)
-middle	0.170***	0.0437	0.015	0.597***	0.591***	0.537***
	(0.063)	(0.071)	(0.072)	(0.049)	(0.091)	(0.094)
-richer	0.148**	0.056	0.037	0.440***	0.405***	0.374***
	(0.060)	(0.067)	(0.068)	(0.049)	(0.089)	(0.090)
Partner/spouse's education	-0.010*	-0.032**	-0.028**	-0.007*	-0.03***	-0.042***
	(0.006)	(0.013)	(0.013)	(0.004)	(0.009)	(0.009)
Woman's education	0.001	0.042*	0.032	-0.039***	0.000	0.005
	(0.006)	(0.022)	(0.022)	(0.004)	(0.023)	(0.024)
Household own agricultural land	-	-0.195	-0.076	-	-0.291*	-0.368**
		(0.122)	(0.124)		(0.154)	(0.158)
Household own agricultural land × agriculture: woman	-	-0.074	-0.085	-	-0.067	-0.011
		(0.103)	(0.104)		(0.112)	(0.114)
× agriculture: Partner	-	-0.172	-0.181*	-	0.090	0.088
		(0.107)	(0.108)		(0.107)	(0.109)
× woman's education	-	0.010	0.010	-	-0.012	-0.017
		(0.015)	(0.016)		(0.014)	(0.015)

× partner's education	-	0.027*	0.018	-	0.029**	0.032**
		(0.014)	(0.014)		(0.014)	(0.015)
Agriculture: Woman × woman's education	-	-0.001	-0.008	-	0.013	0.013
		(0.011)	(0.011)		(0.015)	(0.015)
Woman's education ^2	-	-0.005***	-0.005***	-	-0.002**	-0.003**
		(0.001)	(0.001)		(0.001)	(0.001)
Household size	-	-0.011	-0.024**	-	0.044***	0.049***
		(0.011)	(0.011)		(0.013)	(0.014)
Polygamy	-	0.242***	0.177***	-	-	-
		(0.051)	(0.054)		-	-
Woman is Muslim	-	-0.468***	-0.227***	-	-	-
		(0.057)	(0.087)		-	-
Rural	-	0.052	0.083	-	-0.090	-0.125**
		(0.065)	(0.068)		(0.060)	(0.061)
No. of older siblings	-	0.013	0.012	-	0.006	0.009
		(0.008)	(0.008)		(0.008)	(0.008)
Married more than once	-	0.203***	0.231***	-	1.054***	1.097***
		(0.046)	(0.047)		(0.061)	(0.063)
First child is female	-	0.025	0.032	-	-0.083*	-0.085*
		(0.041)	(0.042)		(0.047)	(0.047)
First & second children: female	-	-0.072	-0.083	-	0.115*	0.109*
		(0.053)	(0.054)		(0.060)	(0.061)
Alcoholic Spouse/partner	-	0.360***	0.339***	-	0.581***	0.542***
		(0.038)	(0.038)		(0.052)	(0.053)
Woman's physical retaliatory behavior	-	1.22***	1.25***	-	0.674***	0.646***
		(0.102)	(0.103)		(0.067)	(0.068)
Work remuneration – cash and kind	-	0.252***	0.214***	-	-0.025	-0.012
		(0.080)	(0.082)		(0.073)	(0.074)
Constant	-0.158	-0.151	0.0560	-2.06***	-3.21***	-3.65***
	(0.109)	(0.165)	(0.197)	(0.098)	(0.225)	(0.315)
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time×Occupation		Yes	Yes		Yes	Yes
Ethnicity controls			Yes			Yes
Country Fixed Effects			Yes			Yes
Observations	16,112	15,382	15,382	54,967	17,272	17,272
Pseudo R^2	0.017	0.042	0.056	0.015	0.053	0.068
Log Likelihood	-10027.7	-9365.1	-9229.2	-25307.1	-7966.1	-7842.8
Chi-Square	326.4	725.6	957.0	791.8	849.3	1044.1

Notes: Dependent variable is a binary dummy, representing recognition deprivation (1 = deprived, 0 = otherwise). Robust Standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*; Source: Malawi and Peru DHS.

Household Status: Controlling for country and ethnicity fixed effects, the log-likelihood of recognition deprivation decreases by 27.6% (log-odds = -0.323) when a woman is the head of the household in Malawi. Women who were married more than once are also 26% (log-odds = 0.231) and 199.6% (log-odds = 1.10) more likely to be recognition deprived in Malawi and Peru, respectively. For every year the woman's partner/spouse stays in school, her chances of recognition deprivation decrease by 2.8 (log-odds = -0.281) and 4.1% (log-odds = -0.423) in Malawi and Peru, respectively. We find women's own years of education do not significantly influence her recognition deprivation. Thus, we explore a non-linear route of impact for women's education on odds of recognition deprivation. Jewkes (2002, p. 1423) observes higher female education shaped as an inverted U-curve, to be protective at the lowest and highest education levels, conferring on women, social empowerment, self-confidence and resources use in the society. Thus, we include a squared measure of woman's education. Controlling for country-fixed effects, we observe a 0.5% (log-odds = -0.005) and 0.3% (log-odds = -0.003) decrease in the likelihood of deprivation with more years of women's education for Malawi and Peru, respectively.

Age: Controlling for country effects, we find one additional year in age decreases the likelihood of deprivation among women in Malawi by 2.1% (log-odds =-0.021). Spouse age in Peru was found to significantly increase chances of deprivation by 0.8% (log-odds = 0.008).

Wealth: Using a wealth index[38] as proxy for household wealth, we identify significant relationships between lower wealth status and a high likelihood of recognition deprivation in Peru. According to Sraboni, Malapit, Quisumbing, and Ahmed (2014, p. 12), women in poor households are more likely to be involved in agriculture, in this sector, however, they are frequently resource and autonomy constrained. This in combination with relatively high levels of income inequality in Peru may cause deprivation. This is not the case for Malawi, where the effect of wealth dissipates once we include other controls.

Occupation: Controlling for country effects, the model results show that women employed in agriculture are 21.7% more likely to be recognition deprived in Malawi (log-odds = 0.196). In Peru however, women in agriculture have 34.8% lower chance of recognition deprivation (log-odds = -

[38] The wealth index is the composite measure of a household's living standard expressed in quantiles, using data on household ownership of selected assets, housing construction materials, types of water access and sanitation facilities (Rutstein and Johnson (2004, pp. 1–77)).

0.428). Further analysis revealed that women in households that own land are 30.8% (log-odds = -0.368) less likely to be recognition deprivation in Peru.

Household Characteristics: Using women remuneration as a proxy for personal economic empowerment, we are surprised to observe that women who receive a remuneration (cash and in-kind), are 23.8% more likely to be deprived in Malawi (log-odds = 0.214). Recognition deprivation also increases by 19.4% (log-odds = 0.177) for women in polygamous marriages and decreases by 20.3% for Muslim women in Malawi (log-odds = -0.227). We also note that women with larger households are more likely to be recognition deprived by 5.1% in Peru (log-odds=0.049) while it decreases the likelihood of deprivation in Malawi by 2.3% (log-odds= -0.024). Unlike in Malawi, giving birth first to a girl decreases deprivation chances by 8.2% (log-odds = 0.085) but if the first and second children are both female, the chance of recognition deprivation increases by 11.5% in Peru (log-odds = 0.109).

We observe women retaliatory responses towards violent spouses increase likelihood of recognition deprivation by 248.5% (log-odds = 1.25) and 90.9% (log-odds = 0.646) in Malawi and Peru, respectively. We also notice that spouse/partner alcohol abuse increases the likelihood of recognition deprivation by 40.4% (log-odds = 0.339) and 71.9% (log-odds = 0.542) in Malawi and Peru, respectively. Controlling for country-fixed effects, we observe rural women have 11.7% less likelihood of recognition deprivation (log-odds = -0.125) in Peru only.

Nonlinear effects: We include social-demographic, socioeconomic and time interactors to explore their indirect impacts on human recognition. However, we find weak and contradictory relations between the effects of our interactors and recognition deprivation in both countries, indicating that other direct/indirect pathways may have more influence. Particularly, we find weak relations between land ownership and spouse/women education on recognition deprivation. Although the association between household land ownership and husband education increases recognition deprivation by 3.3% (log-odds = 0.032) in Peru, we do not find such relationship in Malawi.

Discussion

Findings from our study support significant links between human recognition deprivation and social-demographic and socioeconomic factors of women in Malawi and Peru. For both countries, more years of spouse/partner education reduces the likelihood of recognition deprivation. One reason could be, as Jewkes (2002, p. 1425) notes, that education supports social empowerment. Societies with stronger ideologies of male dominance may likely raise men who hold conservative views about women's value in the society leading to women recognition deprivation. Just as Jewkes (2002, p. 1425) argues for educated women regarding liberality and autonomy, highly educated men may also likely to be liberal about their ideas on the roles and value of women within the society and act to provide women with more human recognition. It will be interesting to analyse other pathways in which spouse/partner education plays a role in recognition deprivation for women. Moving to women's education, we find a small non-monotonic relationship (inverted U-shaped) between women's education and recognition deprivation. This is consistent with studies on women empowerment (Samarakoon & Parinduri, 2015, pp. 428–442), partner violence (Flake, 2005, 2005, pp. 353–373; Wilson, 2013, pp. 3–18), social and human development (Jewkes, 2002, p. 1425). That is, women's education as a non-monotonic resource may be harmful at lower levels. Similarly, Mocan and Cannonier (2012, p. 17), Emran et al. (2014, p. 481) and Flake (2005, p. 364) observe positive effects of women's education on freedom of choice, value recognition and women empowerment in Sierra Leone, Vietnam, and Peru.

In both countries marrying more than once puts women at risk of recognition deprivation. Mkandawire-Valhmu et al. (2016, p. 16) argue women in Malawi have limited income opportunities. To escape a life of extreme poverty, they enter less than favourable second or third marriages to provide food security for themselves and their children (Mkandawire-Valhmu et al., 2016, 16). Furthermore, we argue that to avoid the social stigma of divorce and as an avenue to access resources, women in both countries may take up the option to re-marry, limiting their bargaining power and exposing them to negative recognition. Our finding is also supported by Dhakal, Berg-Beckhoff, and

Aro (2014, pp. 77–78). They find that women who have been married more than once have higher risks of experiencing partner violence and contracting sexually transmitted diseases.

Including household characteristics, we observe, consistently in both countries, that women's physical retaliatory responses towards spouses increase the likelihood of recognition deprivation. As in other studies, we also find strong connections between alcohol use and recognition deprivation (Atteraya, Gnawali, & Song, 2015, p. 1236; Barchi, Winter, Dougherty, & Ramaphane, 2018, 12; Flake, 2005, p. 366; Sedziafa, Tenkorang, & Owusu, 2017, 11; Tumwesigye, Kyomuhendo, Greenfield, & Wanyenze, 2012, p. 399; Wilson, 2013, p. 7) and observe heterogeneous patterns of associations between human recognition and household size in both countries. Although, research implicates large household size in violence studies (Barchi et al., 2018, 12; Flake, 2005, pp. 365–366; Jewkes, 2002, p. 1423) and thus, contribute towards recognition deprivation for women, this finding is only supported for Peru in our analysis.

Other heterogeneous patterns refer to woman's age, spouse/partner age, wealth, agricultural land ownership and children sex composition. Consistent with findings of Simiyu (2013, p. 339) and Grabe et al. (2015, p. 15), that women in female-headed households enjoy full control over decision-making for productive resources, women who head their own households are less likely to be recognition deprived in Malawi. Furthermore, we identified Muslim women in Malawi as less likely recognition deprived. One explanation could be the existence of a matrilineal[39] land inheritance system within the ethnic groups practicing Islamic religion in Malawi. Such inheritance systems may confer better human recognition status among these women. Also for Malawi, we find polygamy a significant factor of recognition deprivation in line with various studies on violence against women (Hilliard et al., 2016, pp. 1682–1703; (Barchi et al., 2018, 2; 2016, p. 1687; Issahaku, 2017, 1; Mkandawire-

[39] Within the matrilineal system in Malawi (Berge, Kambewa, Munthali, and Wiig (2014, p. 62)), land and other inheritances are passed on through the maternal line giving women greater control over resources. In Malawi, the Chewa, Yao, Ngoni and Lomwe are matrilineal tribes but only the Yao tribe practice both matrilineal inheritance and Islamic religion. Also see Phiri (1983, pp. 257–274) on lineage system in Malawi.

Valhmu et al., 2016, 8-17). One reason could be the stress of polygamy on household resources, resulting in resource conflicts. Another could be the influence of norms which shape hierarchal behaviour of wives on human recognition provision in the household i.e., wives married as second or third wives may not have equal entitlements and thus, influence. Going forward, we find that cash and in-kind forms of women's remuneration increases chances of recognition deprivation in Malawi only. According to Mkandawire-Valhmu et al. (2016, pp. 8–9), women farmers in Malawi reported several instances where personal economic empowerment in form of remuneration had resulted in spouse/partner control behaviours with spouse/partner taking away their revenues. Consistent with Flake (2005, p. 356) we find rural women in Peru are less likely to experience violence but do not find such relationship in Malawi.

In both countries, women employed in agriculture are significantly affected by human recognition transactions. Particularly in Malawi, women employed in agriculture are likely to be recognition deprived. The effect is consistent in model 1, 2 and 3 for Malawi and only consistent in model 1 for Peru. One explanation why this is different in Peru could be the further inclusion of controls and country fixed effects to account for within country variations. Further examining the descriptive statistics for spouse/partner and women in agriculture in both countries reveals, on average, more households working in agriculture and owning land for agricultural use in Malawi compared to Peru. We also observe, on average, more men work in agriculture than women in Malawi. Sraboni et al. (2014, p. 12) observe women's contribution to farm outputs to be undervalued because of cultural norms that support male dominance in control of resources. Marital dependency in a simple bargaining framework argue that men's increased access to resources leads to higher risk of abuse for women due to resource conflict, especially if the resource is limited as is the case with land resources. In the same vein, Flake (2005, p. 365) and Wilson (2013, p. 7) observe that women status, like employment, protects from violence but can also have the opposite effect when their status exceeds what is acceptable by cultural norms within the community in line with status inconsistency theory. Thus, for a given level of resource like land, access/use conflict can arise if both parties work in agriculture with resource alignment on the household and community level, almost always in favour of the man. This is true particularly, if it is believed that she has exceeded a socially acceptable status of autonomy in the community. Thus, we argue that the heterogeneity seen for women in agriculture in both countries could signal conflict in resource access within the household as observed by Palacios-López and López (2015, p. 1175) and Samanta (2016, p. 242).

Summarizing, women are less likely to be recognition deprived if their spouse/partner spends more years in education. However, women's own education has a small non-monotonic impact on likelihood of recognition deprivation(an inverted U shape) (Jewkes, 2002, p. 1425). Nevertheless, women in both countries are likely to be human recognition deprived if they engage in retaliatory violence, have been married more than once and have alcoholic partner/spouse.

We argue that our human recognition profiles have policy implications for human development if analysed side by side. For instance, the studies of Mukherjee and Benson (2003, p. 339), Escobal (2001, p. 506) and Morley (2017, p. 20) on determinants of poverty in Malawi and Peru, point to the importance of women's education in poverty reduction. Similarly, we find significantly positive effects of partner/spouse and women (albeit small in magnitude) education on human recognition deprivation in both countries. We argue that education has a positive impact on improving human recognition and human development with significant effects on poverty. Mukherjee and Benson (2003, p. 339) and Escobal (2001, p. 506) also observe agriculture to be significant factor of poverty in Malawi and Peru, respectively. In spite of the heterogeneous association between women occupation as agricultural worker and human recognition deprivation, we argue that given the significance of the association and agricultural dependency in both countries, women's level of recognition can also affect their ability to access resources within and outside their households as observed by Sraboni et al. (2014, p. 12).

For one, educating women will not be sufficient to reduce human recognition deprivation if the magnitude of impact is not large. Therefore, improving all levels of education (up to tertiary) for both men and women is likely to be effective in improving human recognition levels with positively impact on resource access and significant effects on poverty. Finally, social policies/programs targeting alcohol use and violence are also likely to improve women human recognition levels in combination with educational policies.

Conclusion

We analysed human recognition and outlined linkages to social-demographic and socioeconomic factors of women in Malawi and Peru. Drawing on Castleman (2013) theory of human recognition, we used the Alkire-Foster method to calculate human recognition deprivation levels for women in both countries.

We observe a notable share of women in Malawi and Peru are deprived of human recognition. In both countries, we find evidence connecting human recognition deprivation to education levels of women and spouse/partner, alcohol use, marriage frequency and women retaliatory behaviour. There are also significant heterogeneous associations between women working in agriculture and human recognition deprivation.

Analysing poverty and women recognition deprivation profiles, we argue, women with little education are likely to work in agriculture in Malawi and likely to be poor in Peru, thus likely to be human recognition deprived in both countries. We suggest that improving the status of education for the spouse/partner and woman will be effective in improving human recognition levels by tackling dominance ideologies and fostering social empowerment. Social policies/programs for alcohol use and violence are likely to improve women human recognition levels in combination with overall education improvement. At the minimum, these policies will improve overall human recognition and human development in both countries.

5. The Effect of Human Recognition on Land Access and Child Nutrition: Evidence from Women Farmers in Malawi.

This chapter is written as follows:

Maduekwe, E. & Buchenrieder, G. (2019). The Effect of Human Recognition on Land Access and Child Nutrition: Evidence from Women Farmers in Malawi. (Working paper)

Abstract

Land access is affected by gendered institutions. In agrarian societies, these institutions limit women's land access and influence how women are recognized as human beings. On the household level, these institutional hindrances support a principal-agent bargaining model, whereby one party controls the factors of production and the other party (woman) must bargain for its use.

We demonstrate that this type of non-cooperative bargaining is prevalent in agrarian households in Malawi. Using nationally representative data, we find significant non-monotonous trade-offs between agricultural land access and women's negative human recognition. We also observe that negative human recognition has a detrimental effect on wellbeing, using child nutritional diversity as proxy.

Our study suggests that changes in power dynamics induced by appropriate institutional change will improve women's human recognition. Revising gendered institutions such that they support the enforceable transfer of land access rights to women will reduce negative human recognition provision and improve overall wellbeing.

Keywords: land, women, human recognition, game theory, bargaining, nutrition

JEL codes: C72, D1, Q1

Introduction

Discussions on resource access, e.g. land access[40] in agrarian societies rarely include intangible forms of human development such as human recognition[41]. Yet, human recognition clearly plays a role in resource access and thus, can be associated with development (Castleman, 2016, pp. 136–140; Schweiger, 2015, pp. 144–145). Alkire (2007, p. 347) outlines development as expanding on freedoms that people value and want. These freedoms support individuals' escape from poverty through, for example, access to productive resources. However, the high incidence of poverty and heavy dependence on agriculture for employment in southeast African countries like Malawi, is more often than not, fueled by unequal access to resources such as land (Chigbu, 2015, p. 1070; Kassie, Abate, Langyintuo, & Maleni, 2014, p. 313).

Clearly, agricultural land access and wellbeing are interdependent. This is true for women in general and women famers in particular (Kabeer, 1999, pp. 435–450; Malapit, Kadiyala, Quisumbing, Cunningham, & Tyagi, 2015, p. 1098; Njoh & Ananga, 2016, pp. 89–104). Improved wellbeing includes higher income or better nutrition, especially for children (Mabsout & van Staveren, 2010, p. 783). To improve land access, appropriate institutions promoting women's rights, recognition, and agency are needed (Bhaumik et al., 2016, p. 243). However, Kodoth (2001, pp. 291–292) notes that gendered patterns of agency, including bargaining power in relation to land access are heavily influenced by women's positions in diverse social institutions like family, community, and ethnic group. The feminist theory of intra-household economics reflects this by treating household members as gendered individuals. Gendered resource allocation in households leaves women with power pay-off determined by a series of bargaining positions (Katz, 1997, p. 26). Consequently, power asymmetries between household members become potential threat points with (or without) exit

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[40] Land access in this context is defined and restricted to a bundle of land use rights: The management right, i.e., enter the land and cultivate it and the withdrawal right, i.e., remove harvest after cultivation. Note that land here refer to only agricultural land i.e., farm land.

[41] Human recognition explores the extent to which individuals value, view and treat others as fellow humans Castleman (2016, pp. 135–136).

options for women. Exit options include formal and informal regulations that relate to rights, divorce arrangements, or social networks. They represent recourse/fallback positions for the woman in case of a negotiation breakdown. Thus, in non-cooperative households with non-viable exit options, provision of negative human recognition becomes one way of ensuring limited resource are kept in line with principal (partner) preferences.

Despite the interdependency outlined above, there is little literature linking negative human recognition manifested as humiliation, dehumanization, violence and lack of autonomy for women farmers in Malawi to land access. To the best of our knowledge, this is the first empirical analysis that that uses a bargaining framework to explain how women farmers are detrimentally affected by deprivations in land access, with negative effects on child nutritional well-being.

Given the above, we propose a simple non-cooperative bargaining model of land access and negative human recognition provision for women farmers in Malawi. We argue that in the absence of viable exit options, land access for a woman farmer is determined by, among others, the amount of negative human recognition she accepts within the household. We also show that wellbeing like child nutrition worsens with increasing negative human recognition for women. We provide empirical support using the pooled cross-sectional Demographic and Health Survey (DHS) datasets for Malawi in 2004/05, 2010, 2015/16 and address endogeneity concerns by using a suitable choice of instruments to isolate the effect of negative human recognition.

We contribute to the research on negative human recognition as a bargaining tool for resource alignment as follows: we note that non-cooperative models are best suited to sub-Saharan Africa context where negative human recognition towards women exists. We show that indeed, negative human recognition is positively and significantly associated with increasing land access for women farmers and negatively correlated with child nutrition in agricultural households. Our results present interesting implications for women farmers in non-cooperative bargaining households.

Theoretical framework

Human recognition and related concepts

Generally, human recognition is important for economic development because of the constitutive and instrumental role it plays, through respect, dignity, empowerment, and social capital (Castleman, 2016, pp. 136–138). Castleman (2016, p. 140) observes that respect at the ethnicity or group level affects human recognition at the individual level. Similarly, Grabe et al. (2015, p. 15) note that women with autonomy over resources enjoy respect within their communities. Thus, acts of respect that relate to human recognition definitely acknowledge the inherent value of its recipients as humans. Human recognition is also related to dignity through social-/self-esteem and empowerment. Schweiger (2015, p. 144) sees social-/self-esteem as the feeling of recognition for contributing to a shared agenda and notes that its denial could reshape social relations. Empowerment is described by Kabeer (1999, p. 437) and Ballon and Yalonetzky (2018, p. 1280) as the ability to make strategic decisions within the context of choice. In other words, positive human recognition empowers women, confers them with choices, agency and power. Human recognition is also interconnected with social capital. Social capital is interpreted as the "[…] enabler of trust […]" (Castleman, 2016, p. 142). Wolz, Fritzsch, Shterev, Buchenrieder, and Gomez y Paloma (2010, p. 285) define social capital as "[…] networks, norms and trust, which facilitate information sharing, collective decision-making and action […]". Similarly, Dufhues, Buchenrieder, and Fischer (2006, p. 8) note social capital to involve social structures that facilitate behavior through trust. Particularly, Dufhues et al. (2006, p. 11) observe that social capital is an important determinant of access to productive resources in agrarian communities. These relationships underpin the concept of human recognition and put into perspective women's human recognition, bargaining power and resource access in agrarian communities.

Human recognition and land access

Obviously, agrarian systems that govern land access are gendered and complex (Grabe et al., 2015, pp. 8–15; Mabsout & van Staveren, 2010, p. 783). In sub-Saharan Africa, women are hardly recognized as economic agents, which is visible in the gender gap in agricultural productivity and land assets. Meinzen-Dick, Quisumbing, Doss, and Theis (2019, p. 73) find evidence that women's land rights, bargaining power, and consumption decisions are interrelated. Meinzen-Dick et al. (2019, p. 73) broadly outline land rights as a bundle of potential rights within tenure systems. Tenure systems may be statutory, customary or operate as a hybrid of both. As argued by Schlager and Ostrom (1992, pp. 250–258) potential land rights like use rights may be bundled together as ownership or may be vested in different people. Use rights refer to "[…] the ability or permission to employ an asset […]" (Meinzen-Dick et al., 2019, p. 74). However, within agricultural households, use rights for land can also include management rights, i.e., the right to enter a land property owned by the household and cultivate on it. It could also include withdrawal rights, i.e., the right to remove all or part of the harvest after cultivation. Given these varying versions of property rights, we restrict land access in agricultural households to consist of use, management, and withdrawal rights.

Jayne et al. (2003, pp. 253–275) note significant overall inequality in average household land access in six selected African countries. In most sub-Saharan African countries, mostly men own these bundles of rights. However, these rights could be further extended to women by virtue of marital arrangements, cohabitation, or ethnic customary practices[42]. For instance, Doss et al. (2015, p. 420) show that men own a larger share of land than women in six sub-Saharan African countries including Malawi. Particularly for Malawi, Doss et al. (2015, p. 423) report that the men also hold on average, 76% of land management rights compared to 23% for women. Furthermore, women with sole ownership of land as a proportion of all household documented land is only 17% for Malawi (Doss et al., 2015, pp. 421–423). In the Volta region of Ghana, Duncan and Brants (2004, p. 19) also observe men had greater land access because they are considered, traditionally, as sole custodians of household property.

[42] In Malawi, 66% of the land is held under customary law and kinship identifies who has rights to customary land. Two systems define how land rights are passed on. They are the patrilineal system, dominant in the north where land rights are passed from father to son, and the matrilineal system, dominant in the centre and parts of the south, where land rights are passed through mothers to daughters Kishindo (2010, pp. 89–97).

In agrarian households, land access may have a final influence on women’s status and long-term investment in the next generation’s human capital like children’s nutritional wellbeing. Panda and Agarwal (2005, pp. 823–848) find that women’s property ownership significantly reduces the likelihood of current and long-term physical and psychological violence in one district of Kerala, India. Grabe et al. (2015, pp. 8–10) also report significant links between land ownership, relationship power, and reduced violence. Chiweshe, Chakona, and Helliker (2014, p. 728) note that gendered roles are based on a negotiated social system between men and women. These negotiated social roles have a notable effect on how women are regarded and on what assets they may have for use. Women’s ability to maneuver in this domain creates trade-offs and frictions at the points of economic and social production, creating land access issues when both partners are farmers (Chiweshe et al., 2014, pp. 717–718).

Model specification and objectives

Eswaran and Malhotra (2011, pp. 1222–1223) observe the effect of domestic violence as a bargaining tool for resource alignment. Resource theory within the feminist theory context predicts that in a cooperative model, women with more autonomy and bargaining power will experience more recognition with a greater chance to resource access (Cools & Kotsadam, 2017, pp. 211–212; Eswaran & Malhotra, 2011, pp. 1222–1223). Vyas and Watts (2009, pp. 577–601) argue that within marital dependency, less resources would lead to more deprivation and abuse. Finally, Atkinson, Greenstein, and Lang (2005, pp. 1137–1148) propose a framework of abuse and deprivation dependent on the partner’s gender ideologies and influenced by the degree to which prevailing norms consider abuse as acceptable.

We formulate a simple non-cooperative land access and wellbeing model for a woman farmer in an agrarian household. As argued by Katz (1997, p. 34) and Fafchamps (2001, pp. 80–91), the rationale for outlining resource allocation in the household as non-cooperative draws on three main bargaining features: information asymmetry, enforcement, and inefficiency. Non-cooperative household models are not characterized by Pareto efficiency (Bourguignon & Chiappori, 1992, p. 359; Fafchamps, 2001, pp. 68–96; Katz, 1997, p. 34). According to Katz (1997, pp. 34–35), three main variants of non-cooperative game models are proposed in literature.

However, we focus on the principal-agent model, which describes the household economy as an "employer-employee" relationship, where the principal has significant advantage in aligning household resources by virtue of ownership of the factors of production. Indeed, in the principal-agent model, power is not only asymmetric but exit options are constrained. Principals hold an access monopoly to resources and can only offer agents equal or slightly more than their wellbeing threshold. Katz (1997, p. 35) notes that this model is most significant in agrarian households in Africa.

We propose a model, in which a woman farmer's land access is endogenous when negative human recognition is a viable option available to her principals with significant influence on wellbeing. We use the term principal to refer to persons, a group of people, or an individual in the household who control(s) the household[43] production factors. For simplicity we focus on land as production factor only and assume that the household, i.e., the principal allocates a fixed share of agricultural land to the woman from the total household agricultural land endowment. Thus, we do not try to determine the individual quantity consumed by the woman. We denote the access and wellbeing functions as $A\left(z\left(hr\right)\right)$ and $U_w\left(z\left(hr, l_{ag}\right)\right)$ respectively, where hr represents the woman's negative human recognition level and l_{ag} denotes the share of agricultural landholding available for use and z is a vector of covariates that support wellbeing.

We also assume that the access function $A\left(\cdots\right)$ is increasing in monotonicity and has curvature properties that are increasing quasi-concave in the first order and decreasing in the last order condition. In households with women farmers, we argue that access to agricultural land, A, differs,

[43] Croft, Marshall, and Allen (2018, p. 36) define a household as a group of persons living together in the same dwelling, with one adult male or female as the head of the household and are seen as a single unit. Note that the person who controls the household resource may not necessarily be the identified head of household.

and in contrast to Eswaran and Malhotra (2011, pp. 1225–1230), allocation of resources may be overseen by a principal. In our model, the woman farmer would like to increase her land access. Thus, in restricting her preference, the principal potentially engages in negative human recognition provision. Suppose the woman farmer would like her access to increase from A to A' and is willing to pay a price by accepting negative human recognition, her stock of human recognition decreases with increasing negative recognition, i.e., $\Delta hr = hr - hr' \quad where \;\; hr' < hr$. The final recognition level is denoted by hr' after accepting negative human recognition.

Assuming the principal sets a level of negative human recognition in proportion to the level of land access available, the woman farmer decides, in optimizing her wellbeing constraints, on how much negative human recognition to accept in exchange for potentially extra land access. The principal is modelled as a first mover in line with Eswaran and Malhotra (2011, p. 1230), on the premise that in certain partnership or marital set-ups, women are required to move to their partner's homes and are required to abide by rules that may promote the subjugation of their rights. Given the above, we solve for the woman farmer's land access optimization in the presence of negative human recognition provision and for simplicity, suppress the dependence of this optimization on the principal's utility. Thus, we can define land access as a constrained access optimization that allows the woman farmer to attempt to maximize her land access, given wellbeing constraints and define the minimum reference wellbeing, $U_w\left(\cdots\right)_0$ as a situation without land access in general.

Given that the woman farmer has little or no viable exit option in our principal-agent model, we denote the woman farmer's wellbeing constraint as

$$U_w\left(z\left(hr, l_{ag}\right)\right) \geq U_w\left(z\left(hr\right)\right)_0 \tag{5.1}$$

and assume it to bind. The level of land access will depend on her human recognition level and how much of negative human recognition she is willing to accept by going against set norms in her environment. Thus, the woman farmer optimizes her land access, A, based on wellbeing constraints as follows:

$$\underset{hr}{Max}\ A\left(z\left(hr\right)\right) \quad s.t \quad U_w\left(z\left(hr, l_{ag}\right)\right) \geq U_w\left(z\left(hr\right)\right)_0 \tag{5.2}$$

If equation (2) has a solution, the woman farmer in a non-cooperative household could maximize access to the point that constitutes Pareto efficiency in a principal-agent decision model. At this level, the value of her overall wellbeing due to increased land access will be, at the minimum, equal to her threshold wellbeing, $U_w\left(z\left(hr\right)\right)_0$.

Solving equation (2) requires setting up the Lagrangian to maximize land access, A, as follows:

$$L = A\left(z(hr)\right) + \lambda\left[U_w\left(z\left(l_{ag}, hr\right)\right) - U_w(z(hr))_0\right] \tag{5.3}$$

Equation (3) represents the woman farmer's evaluation of her land access and the contribution of this access to her welfare given wellbeing constraints and non-viable exit options. The shadow price of the wellbeing constraint is denoted by λ and presents the forgone wellbeing. It also represents the woman farmer's marginal opportunity cost of agreeing to accept more negative human recognition. The binding wellbeing presents the externalities arising from internalizing land allocation decision in the household. This is in line with Eswaran and Malhotra (2011, pp. 1225–1230) and supports our argument that acceptance of negative human recognition is the price paid by the woman farmer in her quest for potentially extra land access.

Thus, the woman farmer's land access maximizing first order partial derivatives of (3) with respect to hr and λ becomes

$$\frac{\partial L}{\partial hr} = \frac{\partial A}{\partial z}\frac{\partial z}{\partial hr} + \lambda\left(\frac{\partial U_w}{\partial z(l_{ag})}\frac{\partial z(l_{ag})}{\partial hr} - 1\right) = 0 \tag{5.4}$$

$$\frac{\partial L}{\partial \lambda} = U_w\left(z\left(l_{ag}, hr\right)\right) - U_w\left(z\left(hr\right)\right) = 0 \tag{5.5}$$

Solving equation (4) for λ yields:

$$\lambda = -\left(\frac{\frac{\partial A}{\partial z}\frac{\partial z}{\partial hr}}{1} \times \frac{1}{\frac{\partial U_w}{\partial z\left(l_{ag}\right)}\frac{\partial z\left(l_{ag}\right)}{\partial hr}} \times -1 \right) \tag{5.6}$$

Factorizing equation (6) yields optimal λ^* as:

$$\lambda^* = \left(\frac{\frac{\partial A}{\partial z}\frac{\partial z}{\partial hr}}{\frac{\partial U_w}{\partial z\left(l_{ag}\right)}\frac{\partial z\left(l_{ag}\right)}{\partial hr}} \right) > 0 \tag{5.7}$$

In equation (7), the woman farmer endogenously chooses the acceptable level of negative human recognition in the presence of household agricultural landholding with the shadow price of land access greater than zero and positive. Thus, λ measures the woman farmer's cost of land access given wellbeing constraints in the presence of negative human recognition.

The shadow price or slope parameter λ, shows the first order condition necessary for a maximum. Taking the second order derivative of λ which is sufficient to indicate that the slope parameter is a maximum, yields:

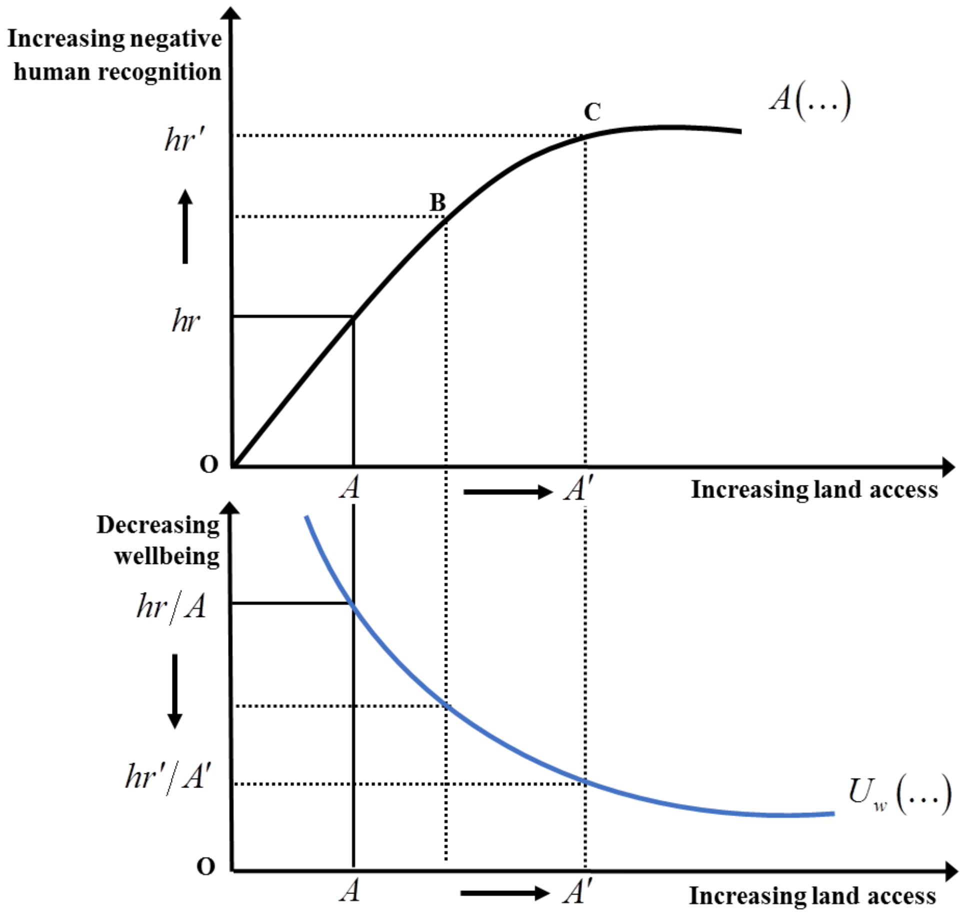
$$\frac{\partial^2 \lambda(hr)}{\partial hr} = \left(\frac{1}{\frac{\partial^2 U_w}{\partial^2 z\left(l_{ag}\right)}\frac{\partial^2 z\left(l_{ag}\right)}{\partial^2 hr}} \right) < 0 \tag{5.8}$$

Equation (8) reveals that additional marginal changes in levels of land access, when the initial marginal shadow price, i.e., the positive slope of land access is steep, will lead to a steeper negative marginal effect of negative human recognition on wellbeing. In general, endogenous land access of the woman farmer and the equilibrium level of negative human recognition depend on the utilities of both, the principal and agent (woman farmer). Thus, for a binding wellbeing, equation (8) is unconditionally true, namely for an increase in negative human recognition, raises the cost of land access (and impact on wellbeing) and so, will force her to economize on accepted negative human recognition.

Figure 1 below illustrates our model. On the horizontal axis is the increasing level of land access. The upper pane shows the woman farmer's land access after optimally accepting the level of negative recognition. The woman's land access, shown as OBC, is a concave function of hr, i.e., for increasing levels of negative human recognition, her land access increases. However, at higher levels of hr, the shadow price of accepting more negative human recognition overwhelms the benefit.

Wellbeing U_w as shown in Figure 5-1, monotonically declines with increasing land access, A. This is because accepting increased negative human recognition, although beneficial to her ability to engage in agricultural activities for income generation, is detrimental overall. Thus, for values, $O < A$, it may not be useful for her to accept negative human recognition, so she will either set the negative recognition she is willing to accept to O or to hr. However, if her wellbeing threshold is binding and the event of negative human recognition provision a possibility, the principal is constrained to $hr < hr'$ and, sets hr' at the largest value of hr. So, when U_w increases, hr' decreases accordingly. For wellbeing within the range $OA'' < A < OA$, equilibrium negative human recognition, hr', will be declining in A.

Figure 5-1 Woman farmers' acceptance for negative human recognition and corresponding wellbeing effects



Source: Authors

Our model demonstrates that in a non-cooperative household bargaining model, a larger agricultural landholding and thus, land access is not accompanied by a monotonous decrease in negative human recognition provided by the principal. With little or no viable exit options for the woman famer, her reservation wellbeing is binding and thus, the principal tries to maintain this with negative human recognition provision. We illustrate this empirically with data from Malawi.

Data and Methodology

We use the pooled cross-sectional data from the Malawi DHS for 2004/05, 2010 and 2015/16. These datasets were collected by multi-stage sampling design and contain information that is nationally representative of households within the 26 main districts in Malawi as shown in Figure 5-2. We limit our sample to the subset of women in agriculture. We generated our main outcome variables of interest namely: a measure of land access and wellbeing.

Figure 5-2 Map of Malawi with districts and administrative zone.

Source: Malawi NSO (2012, ii)

Land access and negative human recognition

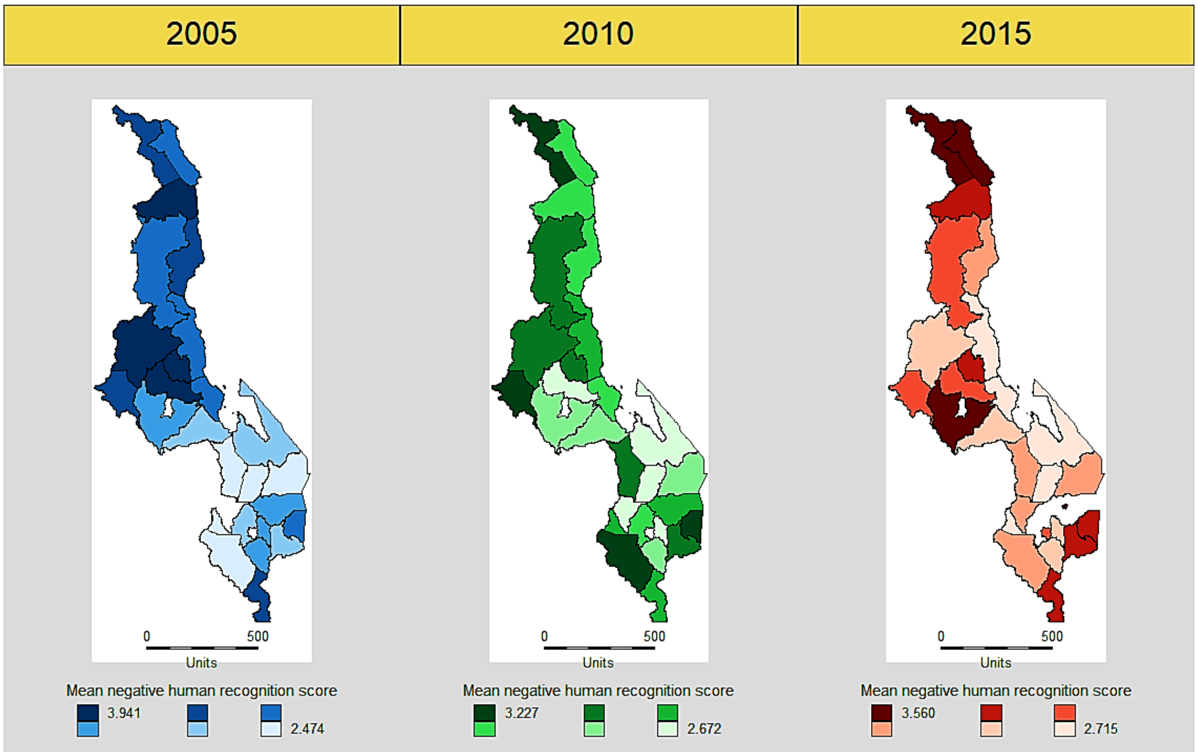
We generate a measure of land access, A, and negative human recognition, hr, as illustrated in the theoretical model above. For negative human recognition, we generate a score of negative human recognition for each woman using indicators of violence, humiliation, dehumanization and autonomy in the self, household and community domains (Castleman (2016, pp. 135–151) and Maduekwe, deVries, and Buchenrieder (2019a, pp. 2–30, 2019b, pp. 2–28)). We rescale the negative human recognition values by 10 for ease of interpretation with 0 as no negative recognition and 10 as highest level of negative recognition. Table 5-1 below shows the distribution of negative human recognition taking into account, the matrilineal system of land access and inheritance in Malawi (Berge et al., 2014, p. 62). In agricultural households, where both partners are farmers, negative human recognition is on average higher for women as compared to households, where just the woman is the sole farmer. Figure 5-3 below shows the distribution of negative human recognition scores by district in Malawi. As expected, negative human recognition is higher in districts in the north, where patrilineal inheritance patterns dominate.

Table 5-1 Negative human recognition scores for women working in agriculture: Two-sample t-test

		Negative human recognition			
	Observations	Mean	SE	SD	Difference
Full					
Only woman is a farmer	1,855	3.051	0.027	1.142	
Both partners are farmers	3,644	3.178	0.018	1.108	-0.127 (0.032)***
All	5,499	3.135	0.015	1.121	
Matrilineal (Yao & Chewa)					
Only woman is a farmer	760	3.067	0.042	1.170	
Both partners are farmers	1,693	3.202	0.027	1.113	-0.135 (0.050)***
All	2,453	3.160	0.023	1.132	

Notes: Negative human recognition scores=0-10. Standard errors in parentheses for difference in Means; SE = Standard error; SD = standard deviation; *Significance level: *** at 1%*

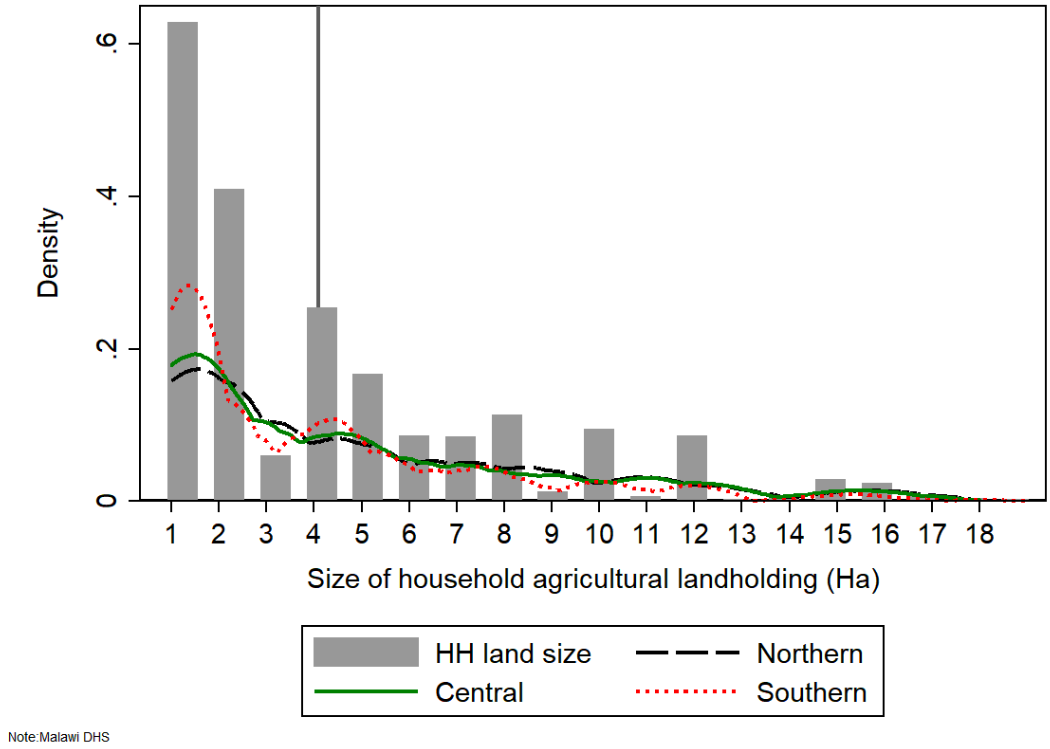
Figure 5-3 Distribution of mean negative human recognition in Malawi



By District; Data source: Malawi DHS

In line with Amarasinghe, Samad, and Anputhas (2005, p. 505), Jayne et al. (2003, pp. 253–275), and Duncan and Brants (2004, p. 19), we proxy land access as household landholding available for agricultural use. Similar to Chamberlin (2008, pp. 6–7), we limit the size of agricultural land to below 19 hectares. We do this to capture small, medium and large sized household-only agricultural enterprises in Malawi. Figure 5-4 below shows the general distribution of agricultural landholding by regions in Malawi. A skewered distribution is evident and varies in size by region.

Figure 5-4 Distribution of household agricultural landholding size, histogram and density functions by regions in Malawi



Notes: Mean household agricultural landholding is shown as vertical line. Kernel density functions for each region: Epanechnikov kernel; HH = household

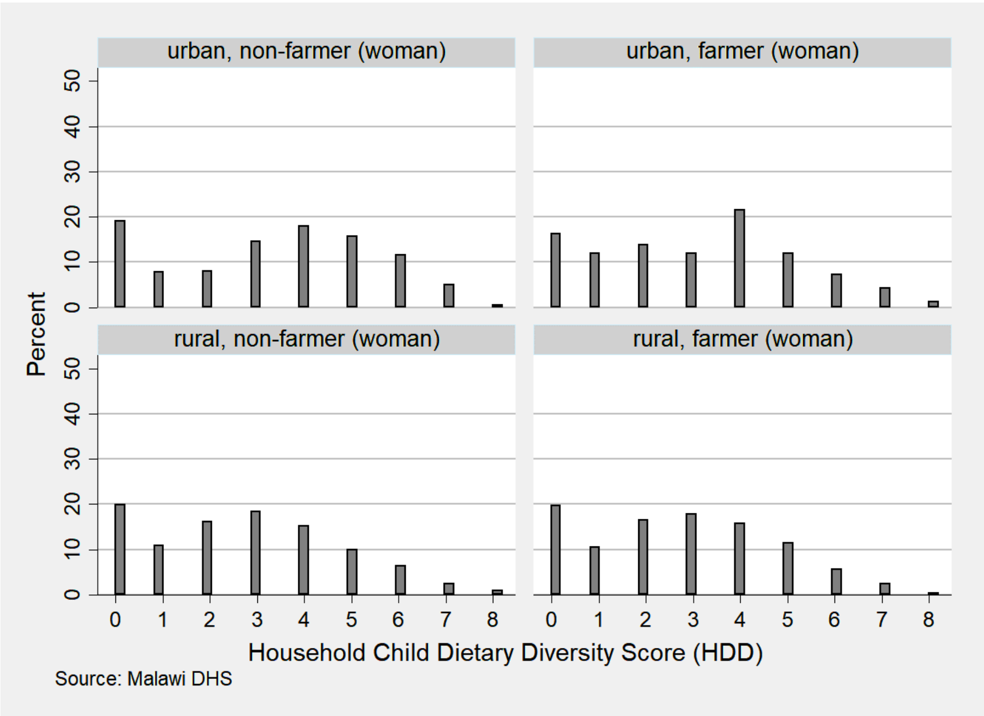
Average household child dietary diversity

Studies show that children's nutritional status is related to dietary diversity and that it is a strong indicator of household nutritional wellbeing (Arimond et al., 2010, 2059; Arimond & Ruel, 2004, p. 2579). Thus, we generated a measure of wellbeing as child dietary diversity (HDD[44]) using data from the 7-day and 24-hrs recall of food groups eaten by only last birth-children aged 0-59 months within the household. Using data on repeated 24-hr recalls of food intake to construct food group indicators, Arimond et al. (2010, 2059) show that the food group diversity indicator is highly

[44] HDD is calculated for households with children 0-59 months as of the time of the survey. An HDD score of 0 includes children still breastfeeding. We argue that this does not really affect the overall average at the district level.

correlated with micronutrient adequacy of women's diets and to children's growth outcomes. As described by Swindale and Bilinksy (2006, pp. 3–15), we grouped food groups into an 8-point dietary diversity measure[45]. We developed a score-based measure that counts one if a child has consumed any food group in the last 24 hours or 7 days, 0 if otherwise. The HDD scores were calculated for each household for all 8-point food groups as the total number of food groups consumed by the child in the household. Figure 5-5 below shows HDD distribution in urban[46] and rural areas in Malawi. Finally, we calculate the mean district HDD for households with women farmers only to be used as a measure of wellbeing.

Figure 5-5 General household child dietary diversity score in Malawi



[45] The 8-point dietary diversity measure is classified as follows: A: Cereal, B: Root and tubers, C: Vegetables, D. Fruits, EFG: Meat, poultry, offal, eggs, fish and seafood, H: Pulses/legumes/nuts, I: Milk and milk products and J: Oil/fats.

[46] Croft et al. (2018, p. 58) outlines DHS classification of urban areas as country-specific. However, a measure of population density is used first, followed by other criteria like percentage of agricultural population, the availability of electricity or piped water, ease of access to healthcare, schools, or transportation.

Estimation

We hypothesize that in a principal-agent household bargaining model, women farmers accept negative human recognition for land access and thus, negative human recognition is higher in households with larger agricultural landholdings. We also hypothesize that this has detrimental effects on wellbeing.

In dealing with potential endogeneity of negative human recognition and land access, we follow the instrumental variable approach. We use as measures, the women's age at first sexual intercourse and their height (difference in median[47] age of first sexual intercourse and height) as instruments. We chose these instruments for several reasons. Cultural, demographic, and anthropological studies have documented harmful practices which guide behavior. Particularly, certain cultural practices are harmful to women and confer on their inferior position from birth, all through life. Wadesango, Rembe, and Chabaya (2011, p. 121) highlight the role of traditional practices such as child marriages in supporting gender violence and negative human recognition as they reduce women to assets belonging to men. The prevalence of female child marriages increases the likelihood of early sexual abuse and exploitation. Wadesango et al. (2011, pp. 124–125) observe that girls married off to men at very young age, used as debt settlement or compensation, stand a greater risk of health complications in pregnancy and violence. Although Malawi has a high prevalence of child marriages and thus, females have a lower age for first sexual intercourse, we argue that this varies randomly across districts, ethnicity, and survey years in our datasets. For women's height, Eswaran and Malhotra (2011, p. 1240) argue that the height of a woman is exogenously determined and is a robust instrument. We argue that these instruments draw its influence solely from how women are recognized as humans.

We also take into account, the matrilineal system of inheritance as practiced by a few ethnic groups in Malawi (Berge et al., 2014, p. 62). Unlike in the patrilineal system, land and other resources in the

[47] We use the median as it provides a better summary measure in our sample in the presence of outliers.

matrilineal system are passed on to the female heir with the maternal uncle controlling its allocation and ensuring it remains within the family. This system creates varying patterns of land access interacting with the woman status in the household. To account for this variation in land access patterns, we estimate a separate model using the sub-sample of women farmers who come from the two largest matrilineal ethnic groups in Malawi, the Chewa and Yao (Bhaumik et al., 2016, p. 243). We instrument for the endogenous nature of negative human recognition in the matrilineal model by also applying the instruments used for the land access model as well as a dummy indicating if the first-born child is female. Das Gupta (1987, p. 77) notes that women who have male children enjoy a higher status in traditional patriarchal societies. Other studies, e.g. Eguavoen, Odiagbe, and Obetoh (2007, pp. 43–46) find high male sex preference for respondents surveyed in Nigeria and excess mortality among female infants in India (Das Gupta, 1987, pp. 77–98). In Uganda, van Campenhout (2016, pp. 587–588) observes that households in which the two first born children are girls, are more likely to have more children in their quest for a boy child. As a result, such households tend to view their female children as having little or no value since they will not be eligible to carry on the family lineage (Jayachandran & Kuziemko, 2011, p. 1485; Kandiyoti, 1988, pp. 274–280). Thus, we harness the varying gender and fertility preferences in matrilineal/patrilineal societies as an exogenous component of human recognition.

The exclusion restriction of the instrumental variable (IV) estimation requires that the relationship between the instruments and our outcome variables be completely addressed by negative human recognition. We argue that our instruments meet this criterion as argued above and as illustrated in our results. We first estimate the ordinary least squares (OLS), the IV-two stage least square (2SLS), and the IV-limited information maximum likelihood (LIML) regression for our outcome variables. For OLS we estimate the following equation:

$$y_i = \beta_0 + \beta_{hr} hr_i + \beta_x X_i + \varepsilon_i \quad (5.9)$$

Where y_i is the outcome variable, hr is negative human recognition score, X is a vector of individual, household and community characteristics, and ε is the error term. β_0, β_{hr}, β_x are the associated vectors of intercept and slope coefficients. We estimate an IV model as follows:

$$hr_i = \alpha_z Z_{ihr} + \alpha_x X_{ihr} + \varepsilon_{ihr}$$
$$y_i = \beta_0 + \beta_{hr} hr_i + \beta_x X_i + \varepsilon_i \quad (5.10)$$

where hr is negative human recognition score, y_i denotes the outcome variables, Z represents the instrumental variables used, while X is a vector of exogenous regressors.

Results

Trading human recognition for land access

We present the key findings from the OLS, the IV-2SLS, and the IV-LIML regressions. A complete list of the control variables and summary statistics is available in Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-6 and Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-7. The comprehensive model results are available in Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-8,Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-9 and Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-10. Key results on land access, overall and accounting for matrilineal inheritance, are presented in Table 5-2 and Table 5-3 below, respectively.

The OLS estimates show that negative human recognition is positively and significantly associated with household land access for women farmers overall and for matrilineal women farmers. That is, a one unit increase in negative human recognition elevates land access by 0.096 hectares. Taking the endogeneity of negative human recognition into account, as shown in the 2SLS and LIML models, the coefficient on negative human recognition remains positive and significant. This implies that negative human recognition increases with increasing land access. Particularly, one unit increase in negative human recognition increases land access by ca. 0.98 hectares. Accounting for matrilineal land inheritance pattern in Malawi, we also show significant results for negative human recognition and land access.

Controlling for endogeneity, negative human recognition is significantly associated with land access in matrilineal households. This is in line with Bhaumik et al. (2016, p. 243), who find conflict in matrilineal landholding settings where land access may be contested by maternal uncles. We report the first stage estimates of negative human recognition and the Wu-Hausman test of endogeneity. For all models, the Wu-Hausman test did not reject the null hypothesis of consistency in the OLS estimates at the 5% level or lower. We check for the robustness of our instruments by reporting the first stage F-statistic. According to Stock and Yogo (2005, pp. 101–105), the F-statistic should be, on average, above the value of 10 in order to rule out the effects of weak instruments. We observe weak instruments for the matrilineal model. However, we report the coefficient from the LIML estimator, which is robust to weak instruments.

Table 5-2 Estimates of land access for women farmers in Malawi

Land access (agricultural landholding in ha)	All		
	OLS	IV-2SLS	IV-LIML
Negative human recognition	0.096**	0.977*	0.979*
(0-10, 0= no negative human recognition)	(0.039)	(0.568)	(0.568)
Endogeneity: Wu-Hausman test (p-value)	-	0.108	0.102
Overidentification: Hansen J-stat (p-value)	-	0.790	0.779
F-stat	88.27	78.74	78.34
R^2	0.369	0.306	0.305
Adjusted R^2	0.365	0.301	0.300
First stage regression:			
Dependent variable is ***negative human recognition***			
Difference from the median:			
- age at first sexual intercourse		0.014***	0.014***
		(0.005)	(0.005)
- height		-0.001***	-0.001***
		(0.000)	(0.000)
F-stat of excluded instruments		13.53	13.15
25 individual/household, 2 time and 9 ethnicity controls	Yes	Yes	Yes
Observations	5,499	5,499	5,499
Degrees of freedom	37	37	37

Notes: Robust standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Table 5-3 Estimates of land access for matrilineal women farmers in Malawi

Land access (agricultural landholding in ha)	Matrilineal		
	OLS	IV-2SLS	IV-LIML
Negative human recognition	0.167***	1.210*	1.539*
(0-10, 0=no negative human recognition)	(0.061)	(0.661)	(0.909)
Endogeneity: Wu-Hausman test (p-value)		0.136	0.136
Overidentification: Hansen J-stat (p-value)		0.108	0.126
F-stat	56.11	47.63	43.38
R^2	0.410	0.324	0.261
Adjusted R^2	0.402	0.315	0.252
First stage regression:			
Dependent variable is ***negative human recognition***			
Female first-born child		-0.075*	-0.075*
		(0.044)	(0.044)
Difference from district median			
- height		-0.001***	-0.001***
		(0.000)	(0.000)
- age at first sexual intercourse		0.013*	0.013*
		(0.008)	(0.008)
F-stat of excluded instruments		6.451	6.451
25 individual/household, 2 time and 2 regional controls	Yes	Yes	Yes
Observations	2,453	2,453	2,453
Degrees of freedom	30	30	30

Notes: Robust standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Human recognition on wellbeing

Table 5-4 presents the effect of negative human recognition on district mean household child dietary diversity. Mabsout and van Staveren (2010, p. 783) observed that individual and household bargaining power can be severely altered by gendered intuitions available at the community or group level. So, if negative human recognition has permeated the fabric of social relations, e.g. on the district/ethnicity level, we can capture its effect on wellbeing at the same level.

We find negative human recognition to be significantly and negatively correlated with wellbeing proxied by household child dietary diversity. That is, agricultural households in districts with high average negative human recognition are more likely to have lower household child dietary diversity after controlling for a host of other predictor variables. As we did not estimate an IV regression for this model, we only interpret our results below as correlates.

Table 5-4 OLS estimates of district mean household child dietary diversity in households with women farmers only in Malawi

Household child dietary diversity (District Mean)	Last child	2nd to last child	2nd to last and last children
Negative human recognition (0-10, 0= no negative human recognition)	-0.015*	-0.045***	-0.046***
	(0.009)	(0.014)	(0.015)
Household owns agricultural land (1 = yes, 0 = else)	0.088***	0.101**	0.109**
	(0.032)	(0.047)	(0.051)
Last child: height-to-age Z scores (0-59 months)	-0.008		-0.020*
	(0.007)		(0.011)
Second to the last child: height-to-age Z scores (0-59 months)		-0.023**	-0.020*
		(0.011)	(0.012)
20 individual/household controls, 2 time, 2 regional & 9 ethnicity controls	Yes	Yes	Yes
Observations	4,750	1,747	1,579
R^2	0.224	0.241	0.240
Adjusted R^2	0.219	0.226	0.222
Degrees of freedom	34	34	36
F Statistics	58.13	22.75	19.00

Notes: Robust standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Other Determinants

We also highlight other factors influencing land access and household child dietary diversity i.e., wellbeing. As theorized and in line with Eswaran and Malhotra (2011, p. 1234), higher levels of education and women remuneration should be expected to improve bargaining positions and status, thus, land access. We observe that partner education significantly increases women's land access even after controlling for endogeneity in the land access models. However, women remuneration in kind and her status as wife decreases land access while household size increases with larger agricultural landholding. Finally, we find agricultural households in rural areas, who own livestock and households with an increasing number of partners working in agriculture are linked to larger land access.

In accordance with Arimond and Ruel (2004, p. 2579), we find children with higher child dietary diversity have lower chances of stunting in households where the second to the last child is under 59 months and households where both, the last and second to last children are under 59 months of age. Finally, we show that household agricultural land ownership is positively and significantly associated with child dietary diversity. Intuitively, agricultural land ownership influences the type of crops cultivated with positive effects on dietary diversity patterns.

Discussion

The empirical analysis supports our hypothesis for the existence of a non-cooperative household bargaining in agricultural households, where women farmers accept negative human recognition for access to land with detrimental effects on wellbeing. As observed by Fafchamps (2001, pp. 80–91), when a woman does not control any factor of production and her fallback position/exit option is compromised, her ability to bargain and align resources beneficial to her wellbeing is limited too.

We find that controlling for endogeneity, negative human recognition increases with increasing land access. This is in line with Jayne et al. (2003, pp. 253–275) who note that intra-household characteristics like power dynamics in traditional structures account for the majority of variation in land access. Our findings are also supported by Doss (2001, p. 2085) who outlines that in non-cooperative households, in addition to short-run profit maximization, individuals maintain a Pareto inefficient allocation status to ensure that they retain long-run control of household resources. Economically, women are also willing to accept negative recognition because of lack of alternatives as observed by Schuler, Bates, and Islam (2008, p. 328) in Bangladesh. As noted by Schuler et al. (2008, p. 331), women take actions to conform to demands and expectations especially if they have no exit options, i.e., with binding wellbeing. This observation is in line with our findings for the land access models.

Fafchamps (2001, pp. 68–96) notes that poor illiterate women, operating in an environment with high unemployment, may accept violence to their own detriment if exit options are non-viable. Similarly, Samarakoon and Parinduri (2015, pp. 428–429) show that the effect of women education on bargaining power in low-income countries depends on improving cultural beliefs and attitudes towards women. We, however, find no significant linkage between women education and land access.

Our empirical results also support the assumption that negative human recognition affects household wellbeing negatively. Within the principal-agent bargaining model, negative human recognition is detrimental to wellbeing as shown by child dietary diversity. This also indicates a failure to reach Pareto efficiency as postulated by Katz (1997, pp. 34–39), as non-cooperative models relying on socially enforced gender rules to produce an equilibrium are harmful to women and support negative human recognition.

Our findings imply interesting policy recommendations. Fafchamps (2001, pp. 68–96) and Malapit et al. (2015, pp. 1097–1120) note that wellbeing factors like child nutrition is weighed as a credible threat point by women in consumption choices and thus, can be improved by bettering women's household bargaining power. We suggest that improving women's exit options would strengthen their household bargaining position. However, this alone, will not eliminate the use of negative human recognition by principals in aligning preferences if it is not accompanied with enforceable rights to resource access.

In line with Mabsout and van Staveren (2010, pp. 783–794) and Wiig (2013, p. 105), reversing gendered institutions and improving land ownership and access has a large potential in improving wellbeing and human recognition levels. From an institutional perspective, the pervasive nature of negative human recognition for women suggests that improvement can be tailored to change, particularly targeting factors that support unequal power relations. From the household perspective, enforcement policies targeting the main providers of negative human recognition would reduce the benefits derived from it. These changes would improve child nutritional outcomes and promote overall wellbeing on the aggregate level.

Conclusion

We provide a non-cooperative model of household bargaining where principals control the factors of production and negative human recognition exist. In the presence of non-viable exit options, women farmers accept negative human recognition for land access in the household with detrimental effects on wellbeing. We test our theory using data for women in agricultural households from pooled cross-sectional data from Malawi DHS 2004/05, 2010 and 2015/2016. Controlling for endogeneity, we find evidence that negative human recognition increases with increasing land access. We also show that negative human recognition on average, correlates with a decrease in household child dietary diversity.

We note that non-cooperative models, particularly the principal-agent model, are most fitted in the sub-Saharan Africa context where negative human recognition towards women prevail. Thus, policies targeting the providers of negative human recognition would improve human recognition and land access for women farmers. These changes would also improve aggregate wellbeing like child nutritional outcomes. Our study is limited in our use of household total land size and aggregate measures of wellbeing. Nevertheless, we argue that the datasets are nationally representative and sufficient to capture the dynamics of negative human recognition of a women farmer and its wellbeing effects within the non-cooperative framework of household bargaining.

6. Random Spatial And Systematic Random Sampling Approach To Development Survey Data: Evidence from Field Application In Malawi .

This chapter is published as follows:

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Abstract

Implementing development surveys in developing countries can be challenging. Limited time, high survey costs, lack of information, and technical difficulties are some of the general constraints that plague development researchers. These constraints can hinder data collection and introduce selection bias into the survey data. We outline a multilevel sampling approach for use in areas where comprehensive information on geographical or household characteristics of local population are not readily available. Our approach includes the use of geographical information systems (GIS) for random spatial sampling and personal digital assistants (PDAs) with a global positioning system (GPS) for household systematic random sampling with random walk. Evidence from our field application in Malawi show that the multilevel sampling approach yields relevant survey data which is comparable to historical and nationally representative values; and supports rapid aggregation of preliminary results after the survey. This multilevel design is cost-effective in implementation and reduces bias avenues in the household selection. Overall, this multilevel sampling approach can be used to generate survey data in developing countries where detailed geographical information and household characteristics data are not readily available. It also presents ways of reducing bias in survey data given budget constraints.

Keywords: Spatial random sampling; geo-spatial data; GPS; GIS; PDA; Malawi; sampling design; development measurement

Introduction

Household survey sampling is vital to development research. In the agricultural and development context, researchers use household surveys to collect information on farming cycles, land use, and crop harvests. In addition to resource use, information on household socio-economic and social demographic characteristics can influence development patterns and thus, is vital to village policy decisions especially for sustainable resource management (Bragança & Cohn, 2019; Herold, Couclelis, & Clarke, 2005). As a result, development survey may use spatial sampling to extract information on household economic and social characteristics as well as information on natural resource use like land or forestry.

Spatial sampling is essential to development studies. Researchers use several spatial characteristics to assess the social and economic conditions of target population (Kondo, Bream, Barg, & Branas, 2014; Vanden Eng et al., 2007). Because it is difficult to sample every population frame such as household or individuals in most studies, researchers must resort to different sampling techniques to capture representative and relevant data (Armoogum & Dill, 2015; Kondo et al., 2014). This sampling difficulty is exacerbated in developing or resource-constrained settings where it is challenging to obtain accurate and up-to-date geographic or household data (Kondo et al., 2014). In rural areas, household geographic data are mostly informal, irregular or even completely absent compared to developed settings and as a result, places severe constraints survey sampling design and creates measurement errors in the final survey data (Bostoen et al., 2007). This can severely constrain survey sampling and can create measurement errors in the final survey data (Armoogum & Dill, 2015; Bostoen et al., 2007). For researchers, it is pertinent to find sampling methodologies, which can derive relevant results in these conditions. High quality nationally representative surveys like the Demographic and Household Surveys (DHS) use sampling methods that are time-consuming and expensive thus, not suitable for smaller or budget-constrained research. In population studies, cluster sampling is the most common method used to obtain representative data (Brogan, Flagg, Deming, & Waldman, 1994; Kondo et al., 2014) , mostly implemented as a two-stage cluster sampling design. In the first stage, census enumeration is used to identify the primary sampling units while in the second stage, sampled households are selected from a household unit listing respectively (Himelein, Eckman, & Murray, 2014). While accurate household unit listings in developing countries are costly to compile, researchers seeking to obtain comparable data in budget-constrained studies could use multistage sampling to reduce the number of sampling sites and techniques like random spatial sampling to reduce the chances of sampling bias in the survey data (Himelein et al., 2014). Random spatial sampling uses sample frames containing identifiable geographic units. The geographic units are selected randomly using a spatial sampling software, and seeks to capture the estimated variable of interest within a minimum number of sampling sites (Kumar, 2007).

Spatial sampling methods using geographic information systems (GIS) are being increasingly adopted in a broad range of research applications, such as for air pollution, climate, agriculture, land use, and population studies (Kassié et al., 2017; Kumar, 2007; Shannon, Hutson, Kolbe, Stringer, & Haines, 2012; Zhao, J., Cao, J., Tian, S., Chen, Y., & Zhang, S., 2018; Zhao, Z. et al., 2018). It is also increasingly combined with other technologies like personal digital assistants (PDAs) and global positioning systems (GPS) for in-field data collection. The use of PDAs, GIS and GPS in social sciences ranges from research applications in land management and health analysis, to socio-economic and agricultural analysis (Anselin, 1999; Kirk, Haq, Alam, & Haque, 2015; Kumar, 2007; Shirima et al., 2007; Vanden Eng et al., 2007). GIS and GPS involve hardware, software and geographical data which when combined, provides users with geographical information of a particular space/place as well as satellite navigation services (Kirk et al., 2015). PDA use for data collection in combination with GIS location services or GPS-generated sampling frames are been documented extensively in development and social science research (Kondo et al., 2014; Vanden Eng et al., 2007).

Further research in social sciences show that combining random spatial sampling with GIS, GPS or with PDA technology can support effective survey sampling and data aggregation. For example, Himelein et al. (2014) outline a random geographic cluster (RGC) sampling design using GIS and GPS technology as key to capturing representative livestock household data from a nomadic population in the Afar region of Ethiopia. Using stratified random spatial sampling on high spatial resolution Earth data, Brink and Eva (2009) show the increasing negative impact of agricultural intensification on natural vegetation in sub-Saharan Africa. The use of GIS and GPS is also been noted extensively in population studies. For instance, Kondo et al. (2014) show that stratified random sampling method with GIS and GPS could reduce selection bias in population data in resource-constrained scenarios. Similarly, Grais, Rose, and Guthmann (2007) show that the sample grid method with a random starting point using GPS provides the fastest and easiest method for data collection for field survey teams and is a quicker and more robust alternative to the traditional "spinning the pen" method. Finally, Shirima et al. (2007) highlight the time-saving and enhanced data quality properties gotten from using PDAs for data entry at the point of collection in scattered rural households in Tanzania.

This article describes a multilevel sampling approach, suitable for survey areas where comprehensive information on geographical or household characteristics and local population data is not readily available. Our article builds on previous research on spatial and systematic random sampling as well as the use of multilevel survey design in developing countries using GIS and GPS technology, thus, contributing to the literature surrounding these topics. First, we use geographical information systems (GIS) with random spatial sampling to generate spatial sampling units. Second, we use personal digital assistants (PDAs) with a global positioning system (GPS) for household systematic random sampling with random walk to generate relevant data for women farmers in Malawi.

The next sections describe our multilevel sampling design, the required field sample estimation and field implementation. Finally, we leverage field survey teams' feedback, interviewer performance indicators from our field results and the comparison of a key variable of interest to explore; and conclude on issues surrounding the preparations and limitations of our sampling approach.

Method

General Research Aim

Our primary research objective for Malawi was to collect information on indicators of human recognition—an intangible novel concept of human development and a key variable of interest (see Table 6-1)– as well as socio-economic and social demographic data (household characteristics, employment and labor force participation, land use, agriculture, consumption, and investment habits) from women famers at the household level. Particularly, Castleman (2013, 2016) defines human recognition as "[…] the acknowledgement provided to an individual by other individuals, groups, or organizations that the individual is of inherent value with intrinsic qualities in common with the recognizer, i.e. recognition as a fellow human being […]". In other words, human recognition address how individuals are viewed, valued and treated by others in the society with significant influence on their wellbeing. According to Castleman (2016), positive or negative human recognition provided in recipients' sphere of interaction, that is negative/positive human recognition in the self, household and community domains, can exert significant effects on the material wellbeing of its recipients. Because human recognition can lead to changes in empowerment, dignity and poverty, which in turn, affect the utility and wellbeing of its recipients, we note that the impact of human recognition on women farmer's wellbeing is obscured if factors influencing negative/positive human recognition provision are not identified (Maduekwe et al., 2019a, 2019b). We argue that if negative/positive human recognition exists in a target population of women farmers, it should be detectible within a sub-sample of the target population, examined in the field.

With this in mind, we start our investigation by isolating the indicators of violence, humiliation, dehumanization, and lack of autonomy, as the indicators of negative human recognition provision, within three domains namely, self, household and community. First, we extract indicators of negative human recognition from secondary data from Malawi Demographic and Health Surveys, herein referred to as Malawi DHS - for 2005, 2010 and 2015 (USAID, 2017b) as shown in Table 6-1. We then include these indicators in the human recognition module prepared for the household questionnaire, as part of the study (see Figure 6-3).

Table 6-1 Domains of negative human recognition and indicators

Domain	Domain indicators	Malawi DHS	Primary data
Self (1)	Person with …		
	Usually decides on respondent's health care.	X	X
	Usually decides on visits to respondent's family/relatives.	X	X
	Usually decides on household purchases.	X	X
	Beating justified if … wife goes out without telling spouse/partner	X	X
	wife neglects children	X	X
	wife goes argues with spouse/partner	X	X
	wife refuses to have sex with spouse/partner	X	X
	wife burns food	X	X
	wife is unfaithful		X
	wife is disrespectful		X
Household (2)	Spouse/partner…		
	doesn't spend his free time with respondent.		X
	doesn't consult respondent on different household matters		X
	is not affectionate with respondent		X
	does not respect respondent or respondent's wishes		X
	jealous if respondent talks with other men	X	X
	accuses respondent of unfaithfulness	X	X
	doesn't permit respondent to meet with female friends	X	X
	tries to limit respondent's contact with family	X	X
	insists on knowing where respondent is	X	X
	Respondent has been…		
	humiliated, threatened with harm, insulted or made to feel bad by spouse/partner	X	X
	pushed, shook, had something thrown at, slapped, punched with a fist or hit by something harmful, had arm twisted or hair pulled by spouse/partner	X	X
	kicked or dragged, strangled or burnt, threatened with knife/gun or another weapon by spouse/partner.	X	X
	physically forced to perform sexual acts respondent didn't want to.	X	X
	has ever had physical injuries because of spouse/partner actions	X	X
	hurt spouse/partner during a pregnancy.	X	
Community (3)	Someone else … physically hurt respondent in the community.	X	X[a]
	respondent during pregnancy in the community.	X	
	Respondent has experienced beating, verbal or emotional violence from other family members and community leaders or officials		X

Source. Malawi DHS (USAID, 2017b), Authors' own; Notes: indicators marked "X" are available in both datasets. a- Indicator also includes during pregnancy.

Next, using data from Malawi DHS for indicators outlined in Table 6-1, we, estimate the human recognition deprivation index (HRDI), headcount ratio, deprivation intensity and negative human recognition scores for women farmers (Maduekwe et al., 2019a, 2019b). We find that on average, 17% of women farmers in Malawi are human recognition deprived with deprivation intensities ranging up to 43%. Deprivation intensities also vary by human recognition domains and geographical location (Maduekwe et al., 2019a, 2019b). Thus, we establish the prevalence proportion (17%) of negative human recognition among women farmers in Malawi and take the next steps to design a suitable multilevel sampling approach to investigate this prevalence in our field data collection.

Study area

Our field study took place in Malawi, a landlocked country in southeastern Africa located at latitude, 13.2543 south and longitude, 34.3015 east. Malawi shares its border with Zambia to the northwest, Tanzania to the northeast and Mozambique to the east, south and west. Malawi's total land area is about 118,000 km2 (45,560 square mile) with an estimated population of about 18 million people. Human development indicators show that about 72% of the Malawian population live below the poverty line (World Bank, 2018b). Agriculture is very important in Malawi (Asfaw, McCarthy, Lipper, Arslan, & Cattaneo, 2016; Munthali & Murayama, 2013). On average, 81% of the Malawian workforce employed in agriculture are women (World Bank, 2018b).

Since our target population are women farmers in Malawi, we outline the state of agriculture and land rights for women farmers in Malawi. Most Malawian farmers cultivate less than 1 hectare where they grow maize, beans, peas, and groundnuts as their main crops (Munthali & Murayama, 2013). In Malawi, women farmers face constraints in land ownership and land use in the short and long-term. This is because a large share of Malawi's land is held under customary law and kinship status is used to identify who has access rights to customary land (Kishindo, 2010). Two main social systems in Malawi define how land rights are passed on: a patrilineal system, where land rights are passed from father to son, and a matrilineal system, where land rights are passed on through mothers to daughters. However, current land access rights for Malawian women farmers do not reflect an equitable distribution of land resources. On average, men hold, 76% of land management rights compared to 23% for women. Only 17% of Malawian women have sole ownership of land, measured as a proportion of all household documented land (Doss et al., 2015). These unequal right in land and resource allocation are influenced by how women are viewed, valued and treated among themselves, their household and community (institutions) as well as their bargaining power in claiming productive resource for use.

Going forward, we establish the administrative and geographical layout of Malawi to facilitate the survey sample mapping. Administratively, Malawi is divided into 28 main districts and 4 main government administrative zones. These districts and administrative zones are located within 3 regions namely north central and southern regions as shown in Figure 6-1.

Figure 6-1 Map of Malawi with districts and administrative zones

Note: The 4 administrative zones are marked by circles; Source: Malawi National Statistics Office (Malawi National Statistics Office, 2008)

First, obtaining GIS information of Malawi's districts, administrative zones and census data is important towards establishing district boundaries and determining the adequate sample size for our survey. Administrative level population or geographical data is vital to robust survey data. Geographical data like boundaries are used to select and set geo-fences of sampling units as well as map households to be sampled in the field, if spatial sampling is included in the survey design. Data granularity such as village-level census data or household listings are used to select sampling units, calculate required sample size and to increase the precision of survey estimates (United Nations, 2005). With this in mind, we obtain census data for the three geographical regions in Malawi from Malawi National Statistics Office (Malawi National Statistics Office, 2008). outlines the official 2008 census numbers with projections for 2017 for each region respectively. It also outlines the percentage distribution of the male and female population by region with regards to the overall population. As of 2008, 51% of the Malawian population were female while 44% of the overall Malawian female population lived in the central and southern region.

Table 6-2 outlines the official 2008 census numbers with projections for 2017 for each region respectively. It also outlines the percentage distribution of the male and female population by region with regards to the overall population. As of 2008, 51% of the Malawian population were female while 44% of the overall Malawian female population lived in the central and southern region.

Table 6-2 Malawi regions with 2008 population and 2017 projections

Region	2008 regional population	% of population	% of population: Male	% of population: Female	2017 regional projections
Northern Region	1,708,930	10%	6%	7%	1,360,195
Central Region	5,510,195	44%	21%	21%	6,046,725
Southern Region	5,858,035	46%	22%	23%	6,384,967
Total	13,077,160	100%	49%	51%	13,791,887

Source: Malawi National Statistics Office (Malawi National Statistics Office, 2008)

In Malawi, each region is divided into districts. These districts are further divided into varying numbers of traditional authorities (TA)s with populations ranging from 4 to over 200,000 people (Malawi National Statistics Office, 2008). However, we could obtain population data down to the TA level only. We did not observe nationally collected population or geographical information beyond the TA level. Given this lack of information on the population size at the village level or geographical data on streets and/or household listings, it is important that we derive a different approach to survey sampling in this limited information context.

Random spatial sampling and location of starting points using ArcGIS 10

We select the main sample regions as the two most populous regions, namely: the central and southern regions of Malawi, because about 90% of the Malawian population live in these two regions. Using population proportional to estimated size (PPES) methodology, we select five districts covering both the central and southern regions of Malawi (see Table 6-3). PPES is a sampling technique that uses a measure of size like population size or census data if available, to determine a sampling unit's probability of selection (United Nations, 2005). Since we had census data on population in the districts for 2008 and projections for 2017, we use PPES to select a fixed number of districts (5) within the selected regions (central and south).

Table 6-3 Sampled Malawi regions and districts with official 2008 population.

District	Region	2008 population
Lilongwe rural	Central	1,230,834
Salima	Central	337,895
Chiradzulu	Southern	288,546
Mangochi	Southern	797,061
Nsanje	Southern	238,103

Source: Malawi National Statistics office (Malawi National Statistics Office, 2008)

The five sampled districts make up about 27% of the overall country population (Malawi National Statistics Office, 2008) (see United Nations (2005) on the calculation of PPES) .

It is important to note that the aim of our study survey was not to provide a representative survey of the whole country but to estimate the prevalence of a human development component, which is human recognition, in a sub-sample of women farmers in Malawi. Going forward, we use ArcGIS 10 (Esri, 2011) to map the five selected district polygons on a base map. Using the sampling analysis tool for ArcGIS 10 (Esri, 2011) called fishnet grids, we superimpose a 25 x 25km grid squares with centroids on the base map of the selected districts and a polygon of the TAs within each selected district (see Thomson, Stevens, Ruktanonchai, Tatem, and Castro (2017) and Galway et al. (2012) on selecting primary sampling units (PSUs) from gridded population data). The TAs in the central and southern region ranges from 3 in Mwanza district to 15 in Lilongwe rural. This excludes Lilongwe city which has 58 TAs and Blantyre city which has 26 TAs.

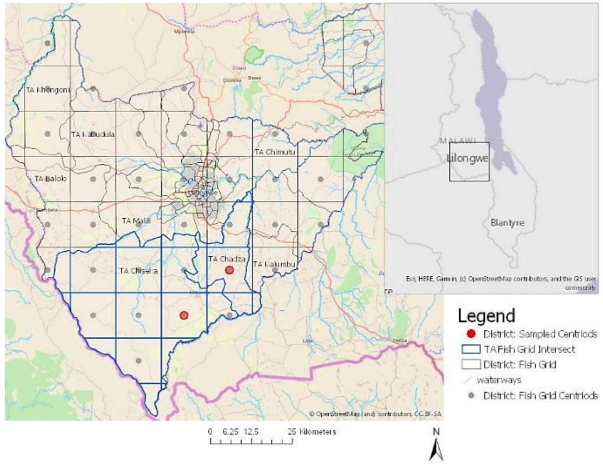
We randomly sample the grid centroids to select the starting points. We then select the nearest village areas to the sampled centroid as the base for the ground data collection (see Figure 6-2 and Table 6-4). It is also important to note that the starting points only indicate the general area where the survey should start from. It neither constrains the number of households interviewed nor sets a village limit boundary for these areas.

Table 6-4 Sampled Malawi regions and districts with 2017 projection and village starting points

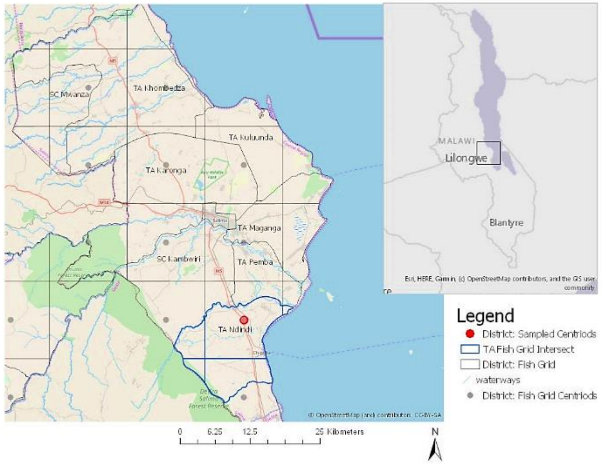
District	Region	2017 projection	Starting points
Lilongwe rural	Central	1,161,408	Mitundu
Salima	Central	445,031	Chipoka
Chiradzulu	Southern	327,038	Namadzi
Mangochi	Southern	1,091,666	Mangochi rural
Nsanje	Southern	295,900	Chididi
Total		1,693,732	

Source: Malawi national Statistics Office (Malawi National Statistics Office, 2008)

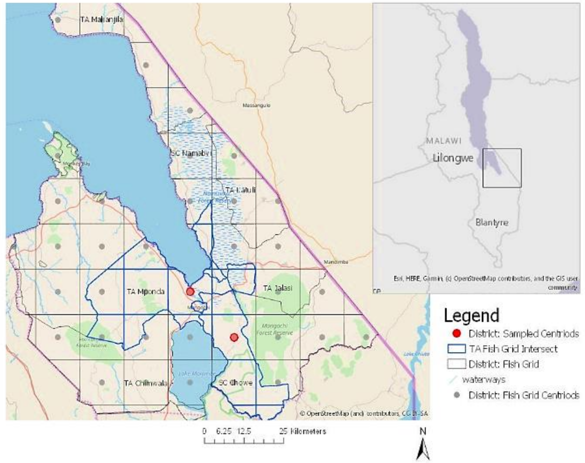
Figure 6-2 Distribution of the sampled areas within the selected grids (District & TA)



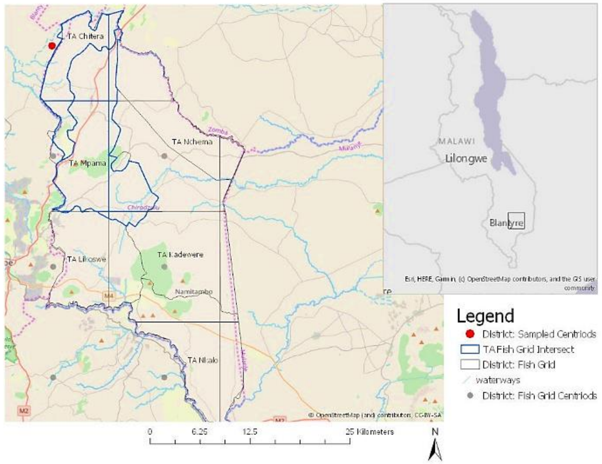
(**a**) Lilongwe



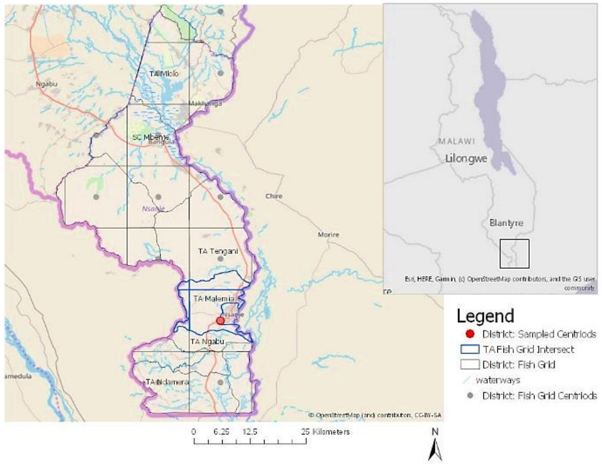
(**b**) Salima



(**c**) Mangochi



(**d**) Chiradzulu



(**e**) Nsanje

Given our study focus, the highly developed urban TAs in Lilongwe district were excluded from the sampling tool. Finally, we establish the TAs to which these starting points belong to and establish their estimated population projection for 2017 as shown in Table 6-5.

Table 6-5 Population projection in TAs with the sampled starting points

District	Region	2017 district projection	TA	TA population: % district	2017 TA projection	Starting points
Lilongwe rural	Central	1,161,408	Chadza	9%	105,900	Mitundu
Salima	Central	445,031	Ndindi	12%	53,012	Chipoka
Chiradzulu	Southern	327,038	Chitera	6%	20,848	Namadzi
Mangochi	Southern	1,091,666	Mponda, Chowe	28%	298,161	Mangochi rural
Nsanje	Southern	295,900	Malemia	5%	14,175	Chididi
Total		1,693,732			250,968	

Source: Malawi National Statistics Office (Malawi National Statistics Office, 2008)

Fieldwork: Survey preparation

Sample size

Our primary research objective was to sample women farmers, collecting information on the indicators of human recognition as well as socio-economic and social demographic characteristics under budget constraints. Particularly, we wish to establish that negative/positive human recognition exists in a sub-sample of women farmers in Malawi as observed in the secondary data (Malawi DHS). However, one challenge to our study objective, as noted by United Nations (2005), is arriving at the right combination of cost savings and precision loss associated with multilevel sampling design such as ours. We note that in cluster sampling, correlation among sampling units may inflate the sample variance and reduce the precision of the survey estimates compared to non-clustered units. As a result, survey sample size must consider the design effect of the sampling method especially for multilevel sampling design. Design effects measure the factor by which an estimate variance obtained from a simple random sample must be multiplied to account for the actual survey design complexity due to clustering, weighting and stratification (Fearon, Chabata, Thompson, Cowan, & Hargreaves, 2017; Salganik, 2006; United Nations, 2005). That is, design effects measure the increase in sample size needed to get the same power as a simple random sample. The design effect for an estimate like, for example, the mean, can be shown as:

$$D(m) = 1 + (b - 1)\rho \tag{6-1}$$

Where $D(m)$ is the design effect of an estimated mean (m), ρ is the intraclass correlation and b is the average cluster sample size. Studies have shown that most design effects range between 2 - 4 and depending on the measure of interest, can be higher as well (Fearon et al., 2017; Salganik, 2006; Wejnert, Pham, Krishna, Le, & DiNenno, 2012). Design effects are usually calculated from existing studies of the target population if the target data are representative and if there is some pre-existing knowledge of the study population (Fearon et al., 2017; Salganik, 2006). Once the design effect is estimated, the sample size needed to estimate a specific prevalence proportion of a particular phenomenon in a target population can be shown as:

$$n = D * \frac{\mu_p (1 - \mu_p)}{se(p)^2} \tag{6-2}$$

Where D is the design effect, n is the sample size, p is the prevalence proportion we wish to estimate, and $se(p)$ is the acceptable standard error (SE) of p. Finally, one can calculate the sample size, corrected for an estimated finite population, n_{adj} ,as follows:

$$n_{adj} = \frac{n}{1 + \left(\frac{n - 1}{N} \right)} \tag{6-3}$$

Where n is the sample size, estimated from equation (2) and N is the estimated population size in the target sample area.

We estimate the design effect from the Malawi DHS for women farmers using the mean negative human recognition scores. DHS data are gotten from two-staged probability sample designs derived from existing sample frames like census data (Croft et al., 2018). DHS sample design uses areas that are homogenous e.g. regions and urban/rural areas, as strata. In the first stage, primary sampling units are selected by population proportional to size (PPS) method within each stratum. In the second stage, a fixed number of households are selected by probability systematic sampling from the complete listing of households in the selected clusters (Croft et al., 2018). The generated probability systematic sampling values are then used to calculate the sampling weights for each primary sampling unit (PSU), household or individual. We normalized the individual weight for women present in the Malawi DHS dataset by dividing the probability variable with 1,000,000 as recommended by the DHS manual (Croft et al., 2018). We then set the complex survey design parameters by applying the primary sampling unit or cluster variable, the stratification variable, and the normalized weight variable using *svy* command in STATA (ICF International, 2012). Finally, we calculate the negative human recognition scores from Malawi DHS using indicators in table 1 above, re-scaling and allowing our final values to lie between 0 (lowest negative human recognition) and 100 (highest negative human recognition score). Then, we calculate the design effects of mean negative human recognition values from the Malawi DHS using the design and misspecification effect function in STATA. presents the design and misspecification effects, DEFF & DEFT and MEFF & MEFT from the Malawi DHS for women, by year and by occupation as farmer or non-farmer. It shows that on average, women farmers have higher negative human recognition than their counterparts in Malawi. It also shows that the design effects (DEFF) and misspecification effects (MEFF) needed to calculate mean negative human recognition for women farmers range from 1.4 to 2.6, and from 1.3 to 2.7 respectively.

Table 6-6 presents the design and misspecification effects, DEFF & DEFT and MEFF & MEFT from the Malawi DHS for women, by year and by occupation as farmer or non-farmer. It shows that on average, women farmers have higher negative human recognition than their counterparts in Malawi. It also shows that the design effects (DEFF) and misspecification effects (MEFF) needed to calculate mean negative human recognition for women farmers range from 1.4 to 2.6, and from 1.3 to 2.7 respectively.

Table 6-6 Estimated design effects for women in Malawi by year and occupation: Mean negative human recognition

	Negative human recognition	Mean	SE	DEFF	DEFT	MEFF	MEFT
2005	Non-Farmer	29.46	0.26	2.12	1.46	2.05	1.43
2005	Farmer	31.04	0.34	2.61	1.62	2.73	1.65
2010	Non-Farmer	29.72	0.28	1.86	1.36	1.74	1.32
2010	Farmer	30.11	0.29	1.76	1.33	1.91	1.38
2015	Non-Farmer	31.10	0.27	1.65	1.28	1.62	1.27
2015	Farmer	31.81	0.26	1.37	1.17	1.38	1.17
	Observations		19,282				

Source: Malawi DHS; Note: SE= Standard error

Going forward, we isolate the design effect by the five selected districts slated for the primary survey from the Malawi DHS as shown in Table 6-7.

Table 6-7 Estimated design effects for women farmers only by the 5 selected districts in Malawi: Mean negative human recognition

Year	District	Mean	SE	DEFF	DEFT	MEFF	MEFT
2005	Chiradzulu	25.24	11.56	1.02	1.01	0.85	0.92
	Lilongwe	30.07	1.22	2.85	1.69	1.69	1.30
	Mangochi	28.45	0.97	1.03	1.01	1.78	1.34
	Nsanje	31.71	1.42	1.45	1.20	1.23	1.11
	Salima	31.09	0.87	0.41	0.64	1.28	1.13
2010	Chiradzulu	28.19	0.74	0.85	0.92	1.80	1.34
	Lilongwe	28.94	1.15	2.29	1.51	1.27	1.13
	Mangochi	24.11	1.48	1.38	1.18	1.11	1.05
	Nsanje	30.57	1.16	0.67	0.82	2.08	1.44
	Salima	29.58	1.06	0.48	0.69	0.78	0.88
2016	Chiradzulu	30.81	1.24	0.72	0.85	1.37	1.17
	Lilongwe	34.58	1.15	2.19	1.48	0.78	0.88
	Mangochi	28.61	1.01	0.90	0.95	0.75	0.87
	Nsanje	28.39	1.29	0.28	0.53	0.65	0.80
	Salima	29.03	1.38	0.70	0.84	1.09	1.04
	Observations	3,987					

Source: Malawi DHS

The average design effect for mean negative human recognition for women farmers in Malawi is approximately 2. According to Salganik (2006), once the design effect is established from existing representative literature and/or data, one can calculate the required sample size with regards to a desired standard error. As initially noted, about 17% of the women farmers in Malawi are human recognition deprived, and thus, we estimate the sample size needed to examine 17% prevalence of negative human recognition for women farmers with a standard error no greater than 3.4 %, a 95%

confidence interval (z-score=1.96) and a design effect of 2. Using eq. (1), we calculate the desired sample size, n, as follows:

$$n = 2*\left(\frac{(0.17)(1-0.17)}{(0.034)^2}\times(1.96)^2\right)\simeq 937 \qquad (6\text{-}4)$$

Thus, we will need a total sample of 937 women farmer respondents for our study. Adjusting for finite population using eq. (2) and plugging in the population totals calculated in Table 6-4 at the district level and TA level, we estimate the final adjusted sample size at the district and TA levels as follows:

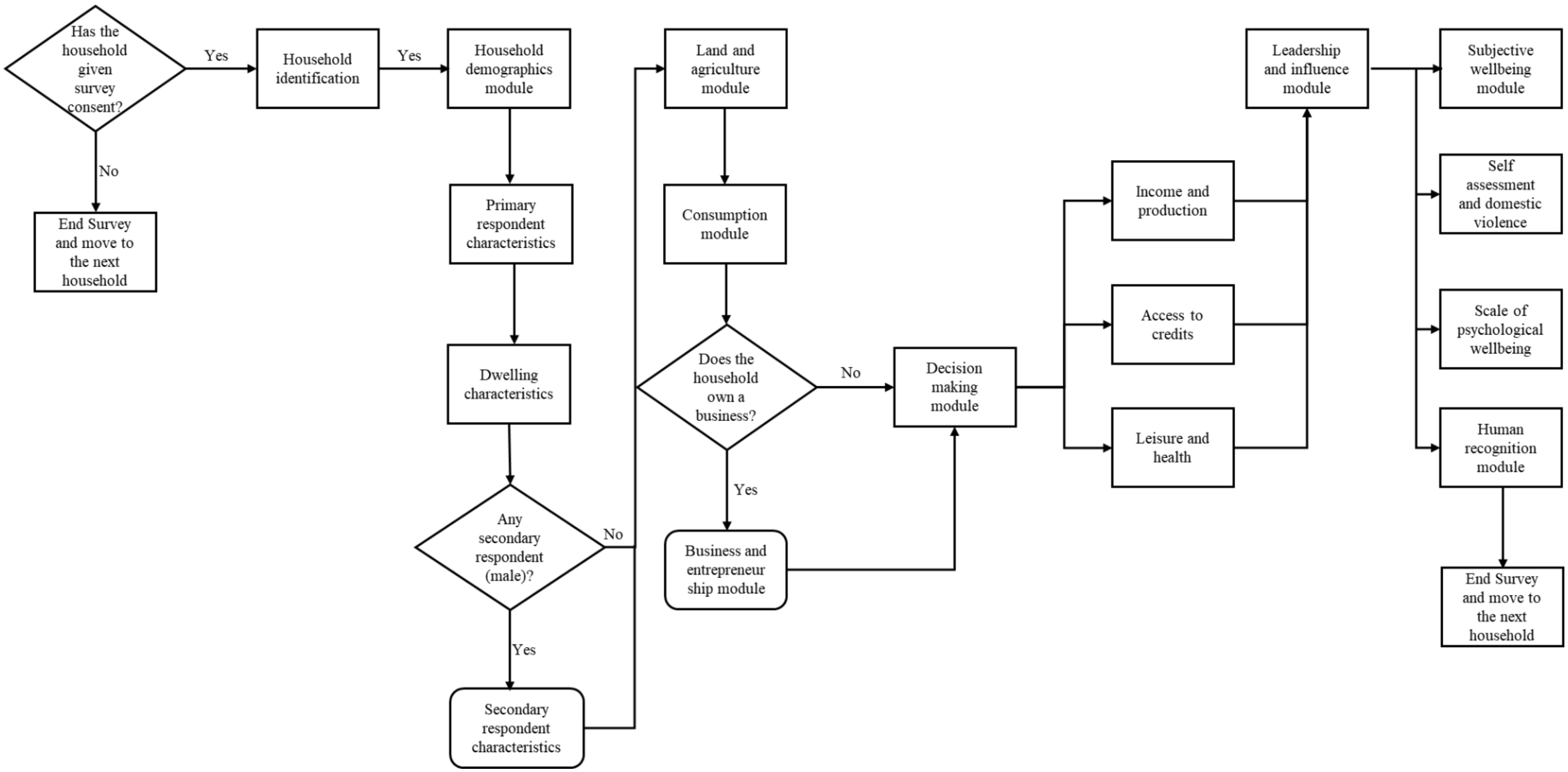
$$\begin{aligned} n(District)_{adj} &= \frac{937}{1+\left(\frac{937-1}{1,693,732}\right)}\simeq 937 \\ n(TA)_{adj} &= \frac{937}{1+\left(\frac{937-1}{250,968}\right)}\simeq 934 \end{aligned} \qquad (6\text{-}5)$$

Thus, in line with Salganik (2006), Grais et al. (2007), Fearon et al. (2017) and Wejnert et al. (2012), we set our desired maximum SE to 3.4% (0.034) with a 95% confidence interval (CI), correcting for finite population. This provides us with a final total sample size between 934-937 respondents (average of 187 women farmers by TA in each district or by district alone).

Field hardware and software

We developed and prepared the household questionnaire (see Figure 6-3) for the field data collection using survey software from Dooblo Limited (Dooblo, 2017). The questionnaire contains seven modules including a human recognition and subjective wellbeing module. We purchased a survey package of 1000 interviews to facilitate our data collection and programmed the household questionnaire modules using the survey software. The questionnaires were transferred to four handheld Android 4.2 based PDAs using the survey software application services. Each PDA was equipped with a standard mobile SIM to support internet connectivity and real-time cloud upload of survey data.

Figure 6-3 Logical flow of household questionnaire



Data transfer was facilitated from the PDA to the computer via cloud upload, and from computer to PDA via synchronization of survey software. The main data capture software consists of a (1) desktop designer application for designing the survey questionnaire, (2) a cloud database for storing the finished questionnaire and collected data in various formats including Microsoft excel, and (3) a mobile application (android- and windows-based) which transfers the finished questionnaires from the cloud database to the PDA and finished data from the PDA to the cloud storage. The PDAs also stored the completed questionnaires on the device memory in the absence of internet connectivity. The data capture software allows the incorporation of logical statements into the questionnaires which were then validated at the point of data entry. Customized error messages, question skipping, password-protection of the questionnaire, and geo-fencing were options available in the software. The software also supported multiple user accounts with unique identifying numbers allowing individual records from field interviewers to be tracked for quality purposes. Overall, the finished field questionnaire was designed to accommodate a range of entries including drop downs, radio selections with single or multiple buttons, and text field entries. They were tested on different screen displays before the commencement of the field survey (see Figure **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-3). Other hardware such as four 500 mAh mini power banks were purchased in addition to two 20000 mAh power banks to account for the unpredictable nature of electric supply within the country. The four 500mAh were assigned to a specific PDA, labelled 1–4 to ensure accountability in case of technical malfunctions.

Training

Female field interviewers were recruited and trained in a 5-day training session to familiarize them with the PDA, GIS/GPS technology and survey content. The recruited female field interviewers were informed on the sensitive nature of the human recognition module with regards to women farmers, and at the time of recruitment, were required to have completed their bachelor's degrees. Specifically, the field interviewers were given the programmed PDAs to practice with, enabling them to gain familiarity with the questions. During the training, emphasis was placed on confidentiality, anonymity and privacy of the female respondents. All necessary protocols needed for an ethical research were presented to the field interviewers to guide them in the data collection. As the field interviewers were required to translate the questions from English to the native language prevalent in Malawi (Chichewa), we ensured that each selected field interviewer was fluent in English and at least two native languages in Malawi including the Yao, Sena, Ngoni, and others. To reduce measurement error that could arise from translating the questionnaire from English to Chichewa, we discussed each question during the training session and field interviewers established consistent wordings that best communicated the questions, to be used in the field interview. The questions in the questionnaire were also simplified accordingly for ease of interpretation and translation. Finally, the field interviewers were given additional training in PDA maintenance, battery charging, troubleshooting, and data backup.

Systematic random sampling of households

The field work for the study was conducted between May and July 2017. Field interviewers used the village center in the starting points as anchor points to form an outward-facing wide circle with the interviewers facing north, east, west and southward from the village centers. This cardinal configuration was swapped for starting points only (five times in total), in anticlockwise rotation i.e., north-facing field interviewer was required to move west, and south-facing field interviewer was required to move to the east etc. In the case of null results from village centers in the starting points like if the village mapped as the starting point was an empty field, the nearest village from the mapped starting point is used as the new starting point for the survey. From the selected village centers, the field interviewer used systemic random sampling with random walk protocol to select the households within the villages. Random walk is a household selection technique that enables face-to-face interviews in areas with no population register, with the assumption that it creates equal sampling probabilities of households (Bauer, 2013). Random walk protocol involves protocol for household selection, which is counting from the first house on the left side of the street to select the household to be interviewed from the random selection key numbers, spreading/fanning out over the village inhabitants, and protocols for non-residential or empty household selections. For instance, if the field interviewer found the next random household to be non-residential, an empty household or a vacant lot, the field interviewer is required to survey the next residence opposite the initially selected residence, to its right, and so on.

Random selection key numbers using Microsoft excel RAND function were generated and used by field interviewers in selecting interviewed households (Excel RAND function returns an evenly distributed random real number greater than or equal to 0 and less than 1. Number ranges can also be set to start from 1 to any maximum e.g. 1–5 or 1–100. A new random real number is returned every time the worksheet is calculated. As of Excel 2010, Excel uses the Mersenne Twister algorithm (MT19937) to generate random numbers for the RAND function.). The RAND skip interval was set between 1 and 5 as the field interviewers reported on the first day that bigger numbers resulted in skipping most of the houses in the villages because of the irregular layout of some villages. When an eligible household with an inhabitant is encountered, the field interviewer enquires about the head of the household. Once the household head is established, the field interviewer interviews the head of the household if female or the female spouse/partner, if head of the household is male. 80% of Malawians live in rural areas and depend on agriculture for their livelihood. Consequently, most women respondents we encountered during the survey were mostly farmers.

Field team and logistics

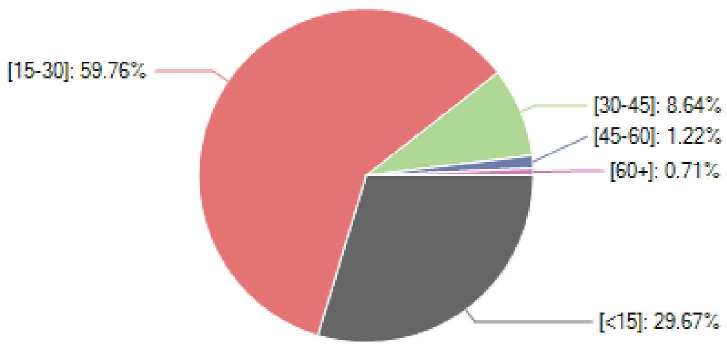
The survey team consisted of one survey vehicle with one team supervisor and the rest of the field interviewers armed with programmed PDAs, information on starting points, random number keys for systematic household selection, and the random walk protocol. Each field interviewer was assigned a PDA number, a user ID and password to facilitate PDA login. A typical data collection day started at 7 am in the morning and ended at 4 pm in the evening and each field interviewer was required to interview about 14–15 respondents every day. Each field interviewer was also required to continue from where they had stopped the household selection from the previous day. As a result, the number of required respondents in the sample district took about 3.5 days to complete. The field interviewers were then moved to the next district to start another round of data collection.

The team supervisor always met with the head of the TAs in the selected survey area the day before to inform them about the study. The interaction with the head of the TAs helps to decrease any suspicion against the field interviewers and made the respondents more receptive to the questions. Eligible households were defined as those having a woman farmer as part of the household leadership structure, either in a dual-headed or single-headed household. Each eligible household can only be selected once in the course of the survey. As most of the approached households were willing to participate in the survey, only a small number of households were replaced by additional household selection. At the end of the survey, all collected data including GPS information were synchronized with the cloud database. Key performance indicators were also synchronized and analyzed. Field interviewer performance indicators like speed of survey completion and quality of answers were monitored using the in-built monitoring system in the survey software.

Field results

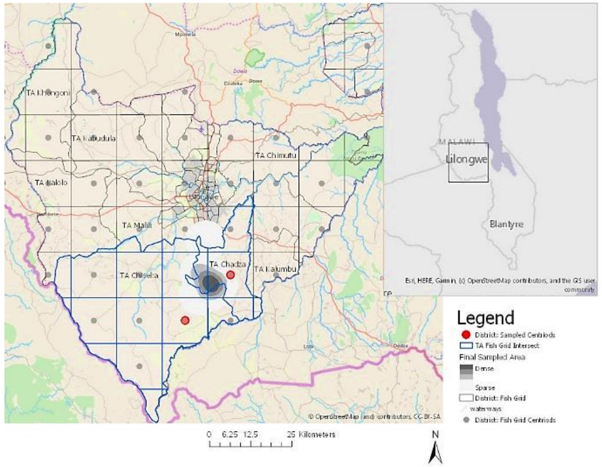
As the end of our field survey, we collected data from two districts in the central region namely: Lilongwe (7 villages), Salima (7 villages); and three districts in the southern region of Malawi: Mangochi (8 villages), Chiradzulu (7 villages) and Nsanje (10 villages). As our method uses village starting points for the survey, the field interviewers were able to fan out across several villages within each TA, in the course of the data collection. Our collected data yielded 933 respondents and about 1% data loss, given our maximum estimated sample size of 937. Our household questionnaire sampled female-only and dual-adult households (those with male and female adults) with women farmers as the main respondents. Each field interviewer interviewed the required number of respondents i.e., about 14–15 respondents per day. Over half of the interviews where completed between 15–30 minutes as shown in Figure 6-4.

Figure 6-4 Interview Average Duration (Minutes)



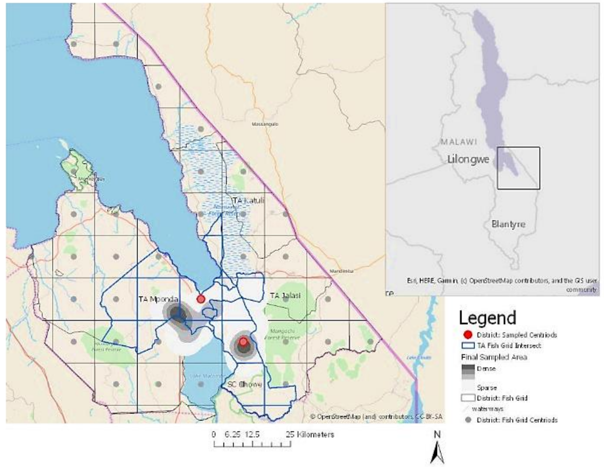
Finished interview GPS coordinates were processed and mapped using ArcGIS 10 (Esri, 2011) on the initial sample grid selections with distance displacements. Figure 6-5 show the distribution of the sampled population data within the selected grid while Figure 6-6 shows an excerpt from some of the sampled villages in Nsanje district.

Figure 6-5 Distribution of the sampled data within the selected grid with distance displacements

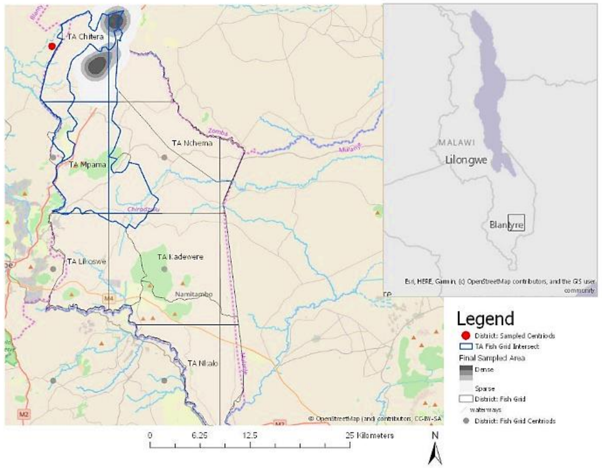


(**a**) Lilongwe

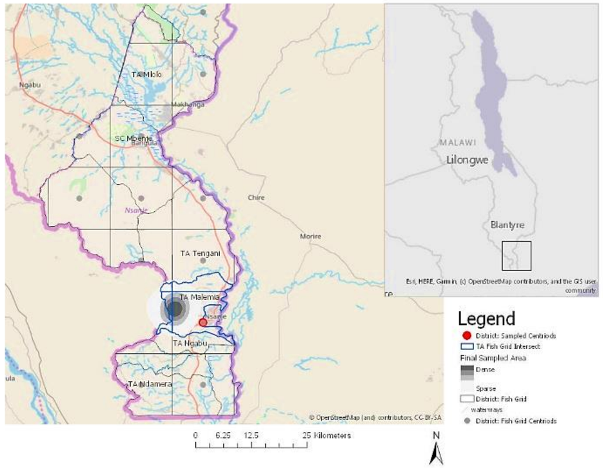
(**b**) Salima



(**c**) Mangochi



(**d**) Chiradzulu



(**e**) Nsanje

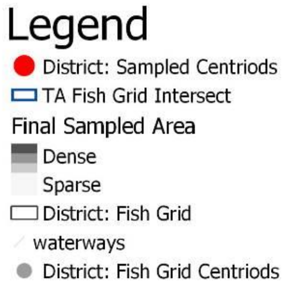


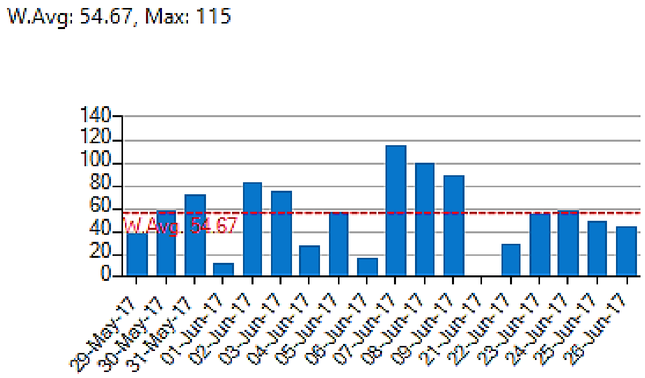
Figure 6-6 Sample excerpt from some of the sampled villages in Nsanje district

Source: Google Earth

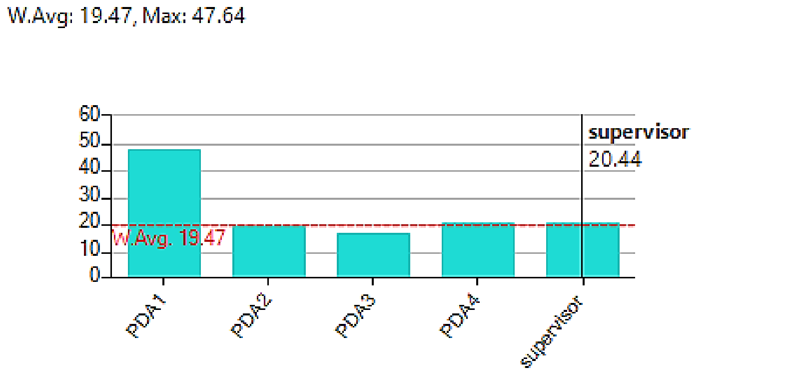
Field interviewer performance indicators

After the survey, the data were downloaded and analyzed using Microsoft excel, ArcGIS 10 and STATA 14. Field interviewer data were also analyzed using software in-built performance indicators. Overall, a total of 18 days were spent in active field work (including travel dates from one location to another) with an average of 54 interviews conducted weekly from the field interviewers. We maintained an average workday length of 6 hours, including an hour of breaktime in between and all field interviewers collected 100% GPS information from the location of interviewed households (See Figure 6-7).

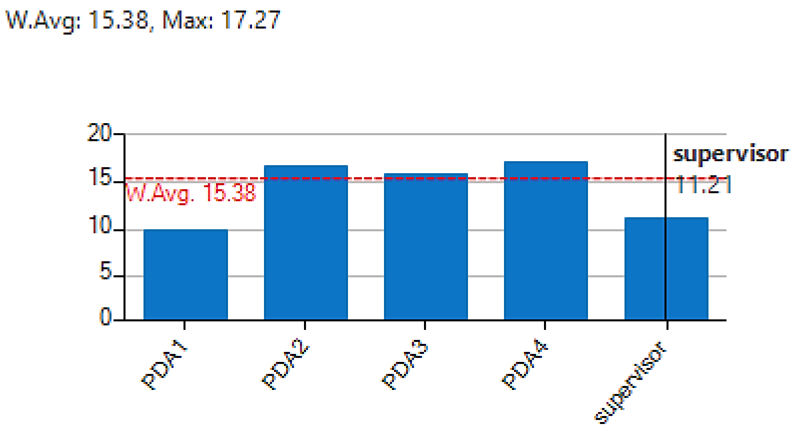
Figure 6-7 Field interviewer performance indicators



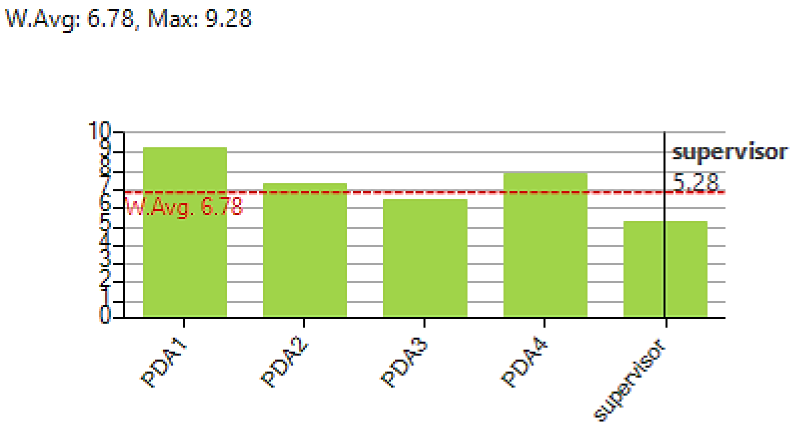
(a) Number of Interviews conducted weekly



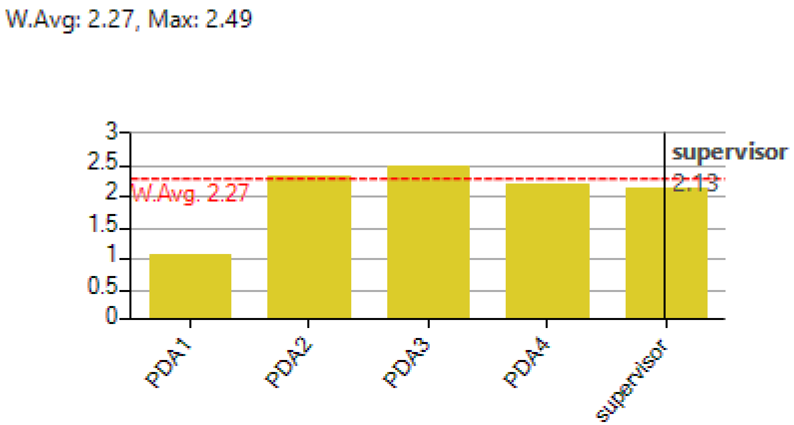
(b) Average Interview Length (Minutes)



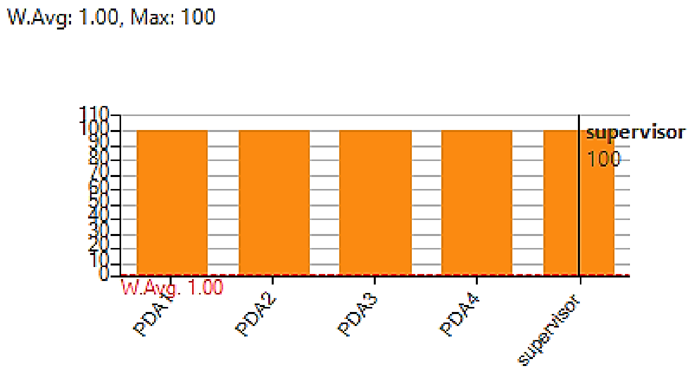
(c) Average Daily Interview Count



(d) Average Workday Length (Hours)



(e) Interview Completion per Hour



(f) Percentage (%)Interviews with GPS location information

Post survey

Data validation using Malawi DHS

The success of a sample design can be checked by evaluating how comparable estimated parameters like the mean and median, are with values extracted from the nationally represented datasets (Kumar, 2007). In other words, how similar are the mean or median values observed in the survey data, when compared to the values observed in the nationally representative data. Thus, we evaluate the performance of our survey design by comparing the mean and median negative human recognition score for sampled women farmers with that, calculated from Malawi DHS for 2004, 2010 and 2015 (USAID, 2017b) (see (Maduekwe et al., 2019a, 2019b) for the definition, indicators and calculation of human recognition scores in general and for women in Malawi). The Malawi DHS dataset contained information on the demographic and socioeconomic status of randomly sampled respondents (women) aged 15-49. Using indicators from the Conflict Tactics Scale (CTS) and domestic violence module (see Table 6-1, above for outline of indicators used in both surveys), we calculate the mean and median negative human recognition score for women farmers for both the Malawi DHS and our collected primary data (Note that the questions from the Conflict Tactics Scale (CTS) and domestic violence module in both the Malawi DHS datasets and the primary survey are the same, except for some word consolidation). We set the multilevel complex survey design parameters for our primary data by applying the primary sampling unit variable (district), the normalized weight variable and the finite population value at the district level using the *svy* command in STATA.

Table 6-8 shows the mean human recognition score calculated for sampled women farmers from our primary survey. Women farmers from these selected areas have on average a deprivation score of 26, which is 2.53 points lower than the pooled average from Malawi DHS for the 5 selected districts.

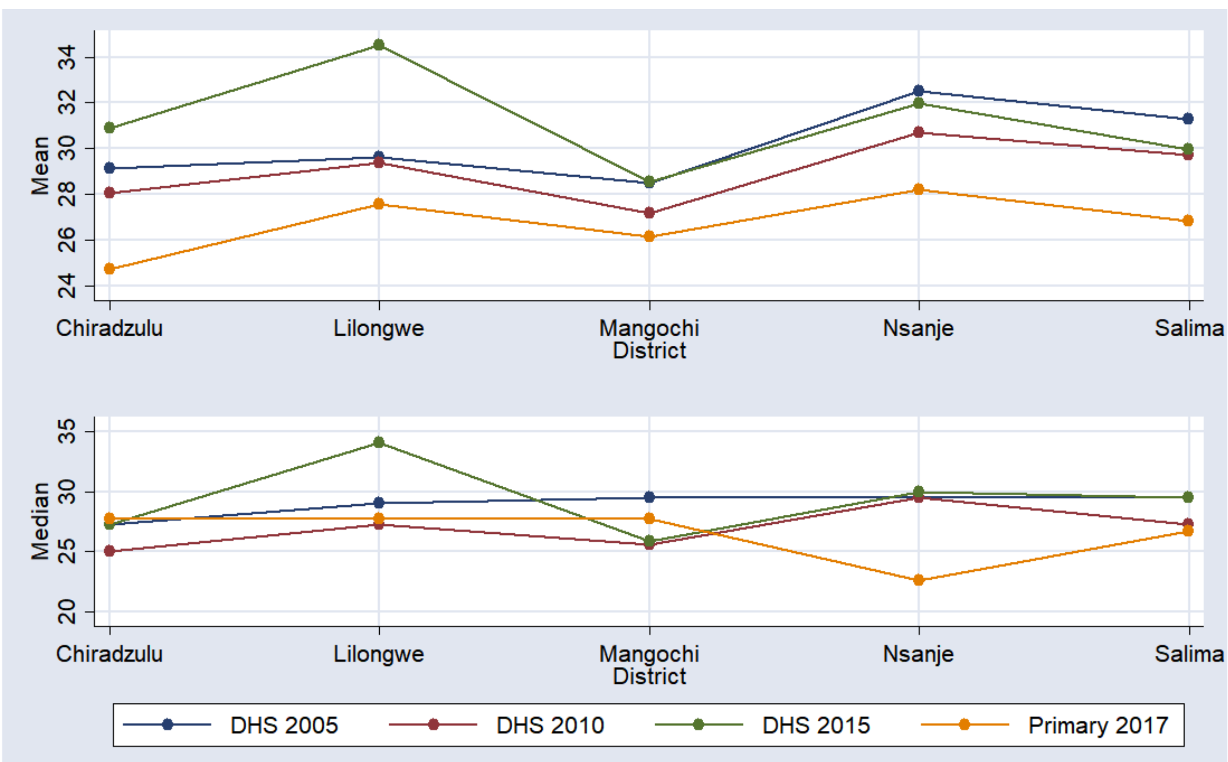
Table 6-8 Mean human recognition score of sampled women farmers from primary survey

	Mean	Standard Error (SE)	95% CI
Negative human recognition	26.76	0.63	25.02 – 28.50
Observations	933		
Population size	1,693,732		
PSU	5		
Design DF	4		

Source: Authors calculations from primary data

We further compare the mean and median distribution of negative human recognition for the five selected districts with that from the Malawi DHS. Figure 6-8 shows the mean and median human recognition score for sampled women farmers from our survey and from Malawi DHS for 2004, 2010 and 2015.

Figure 6-8 Comparison of mean and median human recognition scores calculated from the primary survey and Malawi DHS: women farmers only



Source: Malawi DHS 2004, 2010, 2015 (USAID, 2017b) and 2017 primary data

The yellow line shows the district values from our 2017 survey data while the other lines show the district values from Malawi DHS. The mean and median negative human recognition scores from the 2017 survey dataset fall within a comparable range when examined together with the Malawi DHS for women farmers. Finally, we compare how much the averaged negative human recognition observed in the primary data changed, relative to the pooled average from the Malawi DHS at the district level. Table 6-9 shows the mean negative human recognition and the unit difference from the pooled district average of Malawi DHS for women farmers only.

Table 6-9 Mean negative human recognition and unit difference from pooled district average of Malawi DHS: for women farmers only.

District	Mean (2017)	Mean (Pooled DHS data, 2005-2015)	Unit difference
Chiradzulu	24.71	28.08	-3.38
Lilongwe	27.58	31.20	-3.62
Mangochi	26.13	27.06	-0.93
Nsanje	28.21	30.22	-2.01
Salima	26.83	29.90	-3.07
Observations	933	19,282	
Population size (District)	1,693,732	19,377	
PSU	5	2,185	
Design DF	4	2,130	

Source: Malawi DHS (USAID, 2017b), Author's calculations; Notes: Unit difference= Mean (2017) - Mean (Pooled data, 2005-2015).

The mean negative human recognition score ranges from 24 (Chiradzulu) to 28 (Nsanje) and 27 (Mangochi) to 31 (Lilongwe) in the primary and Malawi DHS respectively. We also compare the unit difference across the different districts in the study and show that, compared with the nationally representative average, unit difference ranges from −0.93 to −3.62 (Note that further analysis of the empirical data derived from this field survey are beyond the scope of this article).

Discussion and limitations of the study

As we derived learned lessons from quantitative and qualitative analysis of our survey data, other limitations to our survey design and approach remains. For example, Kondo et al. (2014) that availability of enough satellite imagery is one of the main challenges facing random spatial sampling for development research. Outdated satellite imagery and map layers often hinder proper spatial mapping and cause field confusion when mapped areas and field locations do not correspond.

Another challenge is that in using a grid method, one runs the risk of selecting only household in high or low density areas (Grais et al., 2007). According to Grais et al. (2007), ideally, a sample grid should be weighed by population. However, the authors found that this method can be costly and time consuming especially if population data is not available. Thus, a grid imposed on an area with both high and low density populations has a higher chance of capturing 50% of the population as the true representation of that population overall. As Malawi is a predominately rural with 80% of the population living in rural areas (ADF, 2005; World Bank, 2018b) and taking quantity and spread of farm lands into account, we argue that the population for women farmers is more uniformly distributed. In addition, our study aim is to collect the sample size required to estimate a fix prevalence value of negative human recognition for women farmers in selected Malawian districts only. As the survey data is not representative of the whole country, we argue that it is not necessary to weigh our sample grids by grid population. Nevertheless, we implemented the survey sample weights, calculated using the finite district population estimates for the survey year.

Random spatial sampling could potentially reduce sampling bias in surveys, however, field interviewers could introduce bias at the household sampling level through field interviewer discretion. As field interviewers are expected to select another household for the survey if the originally targeted household resulted in a null value, the household selection process and thus, field interviewer bias, will most likely vary by study types and by environmental factors. In our study, the combination of various bias mitigating methods from Kondo et al. (2014), Shannon et al. (2012) and Grais et al. (2007) helped mostly reduce field interviewer discretion bias. Field interviewers reported that using village starting points made it easier to pinpoint where to start the household interviews. However, as most residential houses were not symmetrically aligned, village starting points also made it slightly harder to administer the systematic random sampling with random walk. Random walk protocols in household selection create the assumption of equal sampling probabilities of households in the survey vicinity (Bauer, 2013). However, Bauer (2013), Eckman and Koch (2019) and Himelein, Eckman, Murray, and Bauer (2016) argue that random walk can lead to deviations in uniformity which create biases in the sample data. As shown with the random walk routes tested by Bauer (2013), the deviations from the equal selection probability occurs due to the basic routing specifications and the pattern of street network, increasing the possibility of certain houses being sampled more than others. Consequently, sample bias occurs if there are weak correlations between variable distributions and unequal selection probabilities. One way of reducing sample bias is providing field interviewers plotted maps of the interview route to enable researchers control the complete route and reduce selection bias early on (Bauer, 2013). Although we used random walk methodology in our study, we also highlight that our study focuses on rural villages in the selected districts in Malawi, where little or no street networks exists. Most households are on dirt paths and most villages rarely contained long main streets (see Figure 6-9).

Figure 6-9 Examples of household and street layouts encountered in some villages in Malawi

(a) Dirt path in Chididi, Nsanje (b) Google view: Interviewed village, Lilongwe

As a result, the field interviewers were not required to align the length of their random walk routes with the length of the streets as criticized in Bauer (2013). Field interviewer routes winded through from one village to the next as no village or city limit rules were included in the route instructions. Secondly, in our RAND skip list, we generated one random number per household to be interviewed. That means that when the field interviewer selects, for example, the number 2 as the random household number to be interviewed, the next household is selected by following the random walk protocol and counting, using the next new random number on the RAND list. Finally, we check for post-survey bias as suggested by Bauer (2013), by examining the correlations between our variable of interest - negative human recognition - and selection route proxied by the longitude and latitude values (GPS coordinates of the respondents) collected during the survey. Table 6-10 shows the pairwise correlation coefficients between the negative human recognition, the longitude, and the latitude values. We observe that negative human recognition is not significantly correlated with any of the GPS coordinates of the respondents.

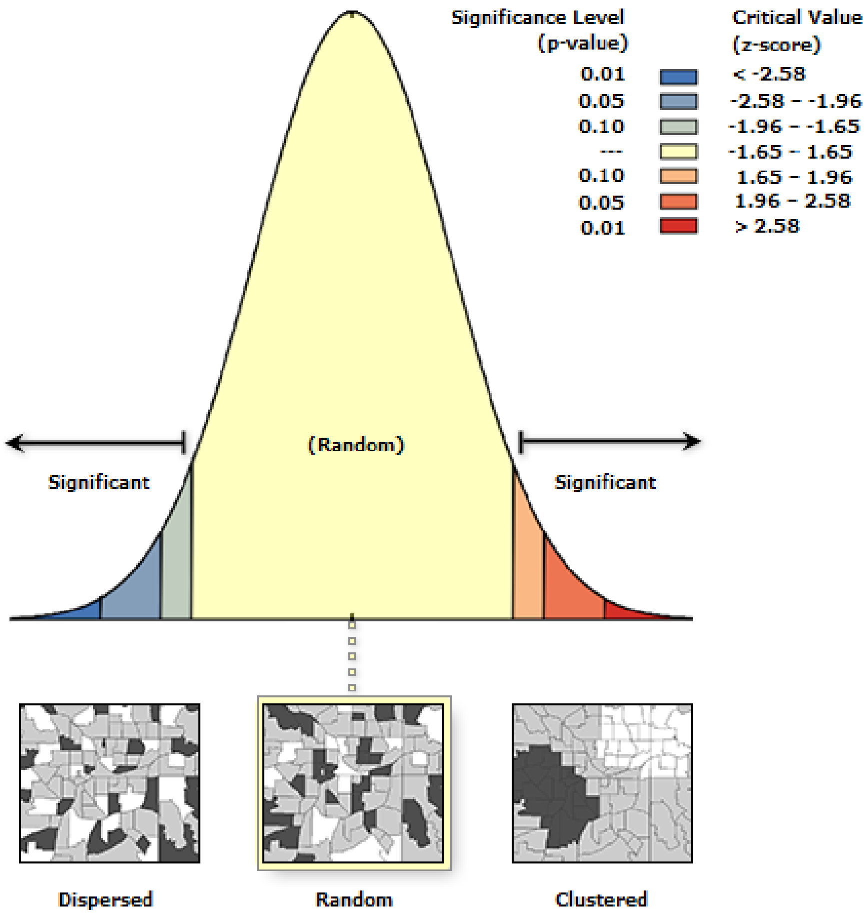
Table 6-10 Pairwise correlation coefficients for negative human recognition, longitude, and latitude of survey data respondents

	Negative human recognition	Latitude	Longitude
Negative human recognition	1.00		
Latitude	-0.02	1.00	
	{0.59}		
Longitude	-0.02	-0.60*	1.00
	{0.49}	{0.00}	

Source: Primary data; Notes: * = Significant at 5% and below; P-values in curly {} parenthesis

We further investigate the presence of spatial autocorrelation in our survey data. Spatial autocorrelation measures the presence of systemic spatial variation in the spatial distribution of that variable of interest. The presence of spatial autocorrelation introduces information redundancy into the survey data if sampled points are very close together and inflates the sampling variance of the estimate, for example, the sample mean. Haining (2001) and Scott (2015) argue that in multilevel survey designs, spatial autocorrelation can be solved by using systematic sampling with random starting points as we implemented in our survey design. In other words, incorporating the systematic sampling method should produce estimates with lover sampling variance. With this in mind, we implement the Moran's Index statistic for measuring spatial autocorrelation in ArcGIS 10 (Esri, 2011). Particularly, the null hypothesis is that the variable of interest being analyzed is randomly distributed among the features in the area of survey i.e., the spatial process involved in the pattern of values coming from our variable of interest is random chance. We set the spatial conceptualization as a zone of indifference and the distance method to Euclidean. Setting the spatial conceptualization to zone of indifference means that features within the specified critical distance (threshold distance) of the target feature will receive a weight of one and influence the computations for that feature. Once the critical distance is exceeded, the weights and the influence a neighboring feature has on target feature computations will diminish with distance (See the documentation on ArcGIS (Esri, 2011)for detailed information on spatial conceptualizations). We also apply the row standardization and set the distance threshold to 25 km, as is with the grid squares (see method section). Figure 6-10 shows the global Moran Index for negative human recognition in our primary survey data with accompanying correlation statistics.

Figure 6-10 Global Moran Index statistics of negative human recognition and correlation statistics



Moran's Index	0.003
Expected Index	-0.001
Variance	0.000
z-score	1.324
p-value	0.186
Input feature class	Sampled Area
Input field	Negative human recognition scores
Conceptualization, distance method and threshold	Zone of indifference, Euclidean and 25 km

Source: Primary data

Non-significant p-value and near zero Moran I statistics indicates that the observed spatial pattern of negative human recognition in the survey data exhibits compete spatial randomness.

However, it doesn't mean that there are no errors in the survey data. Errors such as respondent bias may exist. United Nations (2005) argues that such errors in survey data can occur through the questionnaire design, the data collection method and from the actions of the respondents. Ambiguity in problem question specification, wording, open and closed question formats, order of questions, and response categories are some of the problems which may introduce bias in the sample data. During face-to-face interviewing, respondent bias can be introduced through behavior traits like social desirability. In other words, if the respondent perceives certain events to be socially good or bad, the respondent may decide to under- or over-report the occurrence of that bad or good event, respectively (United Nations, 2005). Another source is the presence of other household members at the interview. In general, these measurement errors can be minimized through field interviewer training, supervision, and workload reduction. As our study focuses on eligible women farmers only, the field interviewers were required to interview the women alone and away from prying eyes. In most cases, the woman was taken to the section of the house or outside where she felt comfortable talking. The field interviewers were also informed of the sensitive nature of the human recognition and domestic violence module and were asked to ensure the privacy of the women before administering these modules.

Finally, Himelein et al. (2016) note the costly and inefficient nature of sampling with replacement for non-response in a developing country context. The authors also note that this method introduces bias into the data for cases of refusal where household replacements follow a non-response replacement protocol like near neighbors that is, selecting the next neighboring structure/household as replacement (Himelein et al., 2016). As we followed sampling with replacement method for the non-response in our survey, we cannot completely rule out the presence of small non-random bias in our survey sample.

Conclusion

We describe a development survey sampling approach for use in areas where comprehensive household and geographical information are not available. We use a multilevel approach with random spatial sampling using geographic information systems (GIS) and household systematic random sampling with random walk using personal digital assistants (PDAs) and global positioning systems (GPS). We trained our field interviewers, familiarizing them with the PDA, GIS/GPS technology and survey content. Data completeness was very high and there was high survey acceptance by the interviewed households, the field interviewers and the supervisor alike.

There are several strengths of our multilevel approach. It reduces the workload associated with pre-survey preparation. It allows random sampling on different levels to minimize selection bias and support the budget constraints of researchers. Researchers could increase or decrease the number of spatial sampling frames as required in the sampling tool. It does not require pre-mapping of target households, allowing researchers to reduce logistics cost associated with visiting a household twice. In our case, we were able to combine household GPS mapping with immediate administration of the survey questions by the field interviewers. Using systematic random sampling helped to further reduce sampling biases by providing information to field interviewers, educating them on what to do in the case of non-residential households or non-response to survey participation. By using randomly generated numbers and random walk protocols, we limited the amount of discretionary decisions field interviewers need to take and reduced interviewer bias in the survey. Seeking permission by informing local leadership like the traditional authorities (TAs) on the nature of the study before conducting the interviews helped to increase the receptiveness of the survey team by the local respondents. The field interviewers reported high compliance from the respondents with answering questions about their socio-economic situations. The field interviewers attributed high response to our willingness to offer an outside listening ear to the women farmers.

The rural nature of the survey conditions and our focus on the agricultural development context in Malawi allowed us to collect quantitative information on various modules which affect land use and wellbeing of women farmers. Further descriptive analysis of our main variable of interest, human recognition, show similar ranges when compared to the same variable gotten from the historical and nationally representative data for women farmers from the surveyed areas.

Using PDAs for data collection over paper questionnaires also provided additional advantages for our research. Paper-based questionnaires can be time-consuming and error-prone. As an alternative, data from PDAs can be quickly collected into a single database, making it easy to carry out quality checks and measure field interviewer performance faster. However, we note certain factors researchers should consider when designing a PDA-based survey. They should include proper logistics planning and allot enough time to field interviewers to finish the interview before moving to another location. For a successful survey, one should ensure the field interviewers are extensively trained and briefed on all survey protocols including fallback safety measures with regards to data backup and switch options for android mobile devices and spare PDAs, in case of technical malfunction. In our case, the GPS system on one of the PDAs malfunctioned towards the last days of the field study. The field interviewer was offered a spare android mobile device with a GPS system and was able to continue the survey data entry from the next days. Finally, questionnaire design should be finished well in advance to provide enough time for extensive deployment and facilitate testing on PDAs.

GIS, GPS and PDAs are simplifying the collection and analysis of population data. They have also become vital for research that aim to combine location data with socio-economic context, human development and research models on other social outcomes. Geographically sampled surveys provide information on important indicators, however, multilevel sampling approaches like ours can be expanded on, further validated and compared with other methods to establish their usefulness in other survey conditions. Our approach, however, shows interesting use in developing countries and resource-constrained scenarios where comprehensive data on geographical and household characteristics are not readily available.

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7. Human Recognition and Land Use Behaviour: A Structural Equation Modelling Approach from Malawi

This chapter is published as follows:

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Abstract

The development of responsible land management requires a proper understanding of how inter-personal relations affect land use choices. This chapter uses the concept of human recognition to reflect these inter-personal relations. We examine the influence of human recognition on land use behaviour and participation in community discourse in communities in Malawi.

In Malawi, women farmers face constraints in land use management and community participation, in the short and long-term because of lack of human recognition. Using structural equation modelling (SEM), we analyse a cross-section of household with 619 women farmers in communities within 5 districts in central and southern Malawi. Results indicate that women farmers with better self/household human recognition and in communities with better institutional recognition adopt improved land use behaviour and have better participation in community discourse.

Our results imply that intangible concepts like human recognition has significant influence land management outcomes. To increase adoption of improved land use behaviour and make land management more responsible in these communities, reforms should reconcile the gap between land owners and land managers. Policies should tackle obstacles facing women participation in community decisions. Finally, better women recognition in the community requires improving community agent's perception of women farmers as value-adders.

Keywords: land use, land management, women farmers, human recognition, Malawi, structural equation models

Introduction

Land management interventions can only be responsible if the relation between people and land is properly understood and if the underlying relationship and land decision dynamics reasons are effectively incorporated in the evaluation of land related interventions (deVries & Chigbu, 2017, pp. 65–73). Contemporary land administration literature models relations between people and land as either a relation of rights, a relation of use or a relation of values (Henssen, 1995, pp. 5–12; Lemmen, van Oosterom, & Bennett, 2015, pp. 535–545; Williamson, Enemark, Wallace, & Rajabifard, 2010, pp. 1–487). In these models, people are captured by the concept ‘subject’ or ‘party’ and is usually considered a rather static entity. Within a group, it is assumed that certain inter-personal relations exist. However, the relationship dynamics which influence the decision to own or use a piece of land are usually not accounted for in land management models. Thus, it is not obvious during land allocation, registration or adjudication processes how to properly assess land tenure relations on an individual level.

Additional discourses on responsible land management and land governance (Zevenbergen, deVries, and Bennett (2015, pp. 1–304) and FAO (2012, pp. 1–47)) emphasize that responsibilities are rooted in multi-disciplinary design. It argues that insights and conventions within land administration are better connected and integrated with theoretical concepts from other disciplines, like sustainable resource management, economics and development studies. In this chapter we introduce the concept of human recognition to improve the comprehension of inter-personal relations and its effects on land use behaviour. Human recognition addresses the extent to which individuals are viewed and valued by others as well as treated based on this value, with effects on recipient’s wellbeing that contribute to aggregate economic development.

Therefore, using structural equation modelling (SEM), we examine the influence of human recognition on land use behaviour in selected communities in Malawi. Particularly focusing on women farmers, we analyse to what extent certain land use behaviour and participation in community discourse are influenced by self/household and institutional human recognition around them. Our study contributes to the literature on the role intangible concept of development like human recognition play in responsible land use and community discourse. It also highlights the role of women farmers as self-agents of perception on barriers to responsible land use vs. the role of community agents in understanding and meeting the needs of their community members.

The rest of the paper is organized as follows: the second section looks at land use and tenure in Malawi. Methodology and descriptive results are presented in the third section and the fourth section presents the hypothesized relationships. The results are discussed and concluded with policy implications in section five.

Land Tenure in Malawi

Malawi developed a National land policy aimed at improving customary land holder's tenure security (Djurfeldt, Hillbom, Mulwafu, Mvula, & Djurfeldt, 2018, p. 605; Peters, 2010, pp. 179–199). Since the new policy was passed towards the end of 2016 and the study data was collected 5 months after, we argue that the effects of the new policy are yet to be reflected. We address the policy in place in the surveyed villages and districts which is the customary land tenure. 66% of Malawi's land is held under customary law and kinship identifies who has rights to customary land, varying across regions and ethnic groups (Kishindo, 2010, p. 90). Two social systems define how land rights are passed on. They are the patrilineal system, predominant in the northern region where land rights are passed from father to son, and the matrilineal system, where land rights are passed on through mothers to daughters. For instance, Kishindo's (2010, pp. 92–97) study of Yao households (matrilineal) residing in Kachenga village, Balaka district, Southern Malawi notes that decision on selection of seed for the next cropping cycle and other minor decisions are carried out by the women. However, purchase of inputs, labour and income disposal were done by the men. Linkages also exists between secure land tenure, decision-making and welfare. Djurfeldt et al. (2018, p. 607) observe influence of female land rights on decision making and household spending patterns in matrilineal village of Khasu. Although Holden and Otsuka (2014, pp. 92–93), Lovo (2016, p. 219) and Holden and Ghebru (2016, pp. 21–28) notes that increased land tenure security increases observable efforts to invest in long-term land development and soil conservation for fertility, these findings were not examined by gender. In a nutshell, findings on the role of women equal partners in responsible land management are lacking and one reason could be the gender roles established in the community that do not fully recognized women as land managers and thus, valued adders in overall land management.

Land use behaviour

Studies have explored the impact of challenges like climate (Arslan, McCarthy, Lipper, Asfaw, & Cattaneo, 2014, pp. 72–86; Asfaw et al., 2016, p. 646; Kassie et al., 2008, pp. 213–232) adoption cost (Sylwester, 2004, pp. 128–140), credit and market imperfections (Carter & Barrett, 2006, pp. 178–199), tenure and community norms on land use (Asfaw et al., 2016, p. 643; Meinzen-Dick et al., 2019, p. 74; World Bank, 2006, pp. 18–30) on responsible land use. For example, adoption of improved agronomic practices such as cover crops and crop rotations, has been associated with better farm performance, improved income and overall environmental sustainability by Knowler and Bradshaw (2007, pp. 25–48), Teklewold, Kassie, and Shiferaw (2013, pp. 597–623), Snapp, Rohrbach, Simtowe, and Freeman (2002, p. 159) and Waldman, Ortega, Richardson, Clay, and Snapp (2016, pp. 1087–1088). Improved land use encompasses the responsible use of land resource, whose exploitation, enhancement and investment is done such that both its current and future potential to meet human needs are advanced (deWrachien, 2010, p. 472). Such land use behaviour retains the land's fertility and supports the production of food and other renewable resources for long term use.

There is increased awareness on the role gender plays in household decision dynamics in adopting certain land use behaviour. For example, Waldman et al. (2016, p. 1094) observe that although households in Malawi are more likely to plant legume crops because of soil fertility and cultural context, female headed households are less likely to do so if they think that it involves more labour inputs. These perceptions reflect the investment responsibilities within households where women are constrained in labour inputs. Meinzen-Dick, Brown, Feldstein, and Quisumbing (1997, p. 1312) argues that gender deferential in agricultural productivity may also be fuelled by education, access, time, labour or other forms of human development. As observed by Kodoth (2001, pp. 291–292), gendered pattern in land use is heavy influenced by women's position in the family, community and ethnic group. That is, how women are viewed and valued in the society impacts women's power dynamics with significant influence on land use behaviour.

Community participation for women is important to improve gender asymmetry. Removal of gendered institutions will support women farmers short and long-term investments in land improvements. However, there are still gaps in addressing land use behaviour through the lens of intangible forms of human development like human recognition for women farmers.

Because of the patrilineal and matrilineal systems that exogenously defined land use and inheritance patterns, Malawi offers an excellent opportunity to examine self/household and institutional human recognition as an intangible influence on land use behaviour for women farmers. Looking from a gender and human rights perspective, such analysis can help better understand some of the constraints faced by women farmers. It will also help highlight how human recognition overall affects and promotes responsible land use behaviour.

Hypothesis and Methodological Approach

Structural Equation Modelling (SEM)

Structural equation modelling (SEM) is mostly used for estimating relationships between multiple endogenous and exogenous factors. SEM with latent variables (LV) further allow the ability to model more abstract concepts constructed as measurement models which cannot be directly captured in a linear model nor be measured by known variables (Denny et al., 2018, p. 10).

SEM has been used extensively to model abstract relationships in agriculture (Denny et al., 2018, p. 10; Jaijit, Paoprasert, & Pichitlamken, 2018, pp. 1–7; Najafabadi, 2014, pp. 225–240) and land use change (Wang, Li, & Yang, 2015, pp. 1–10). Wang et al. (2015, pp. 1–10) employed SEM to assess the effect of land use change on regional climate in southern china and found that vegetation latent variable significantly reduces climate effect. Using SEM, Toma et al. (2018, p. 864) analysed the technological information transfer on uptake of innovative crop technologies and found that economic characteristics including income and farm labour has the strongest effects. Liu and Luo (2018, p. 11) used SEM to analyse the driving factors between farmers land protection perception and land use change in northeast china. The authors found that, among others, external factors like unsecure land rights reduces farmers willingness to engage in land protection. Najafabadi (2014, pp. 225–240) also used SEM to explore the motivating and challenging elements affecting organic farming adoption in Iran through a gender perspective. The author found that attitude to organic agriculture adoption were slightly variable by gender for farmers.

We used the SEM to examine the relationship between self/household and community-reported institutional human recognition, favouring land use behaviour for women farmers in Malawi. Particularly we ask,

1) To what extent is land use behaviour influenced by latent self/household and institutional human recognition?
2) Does latent self/household and human institutional recognition influence women farmers' community participation.

Our SEM consists of two components: the measurement component showing the relationships between the latent variable and its related observed variables and the structural component which describes the relationships between the latent variables. We specify our equation as follows:

The measurement model for self/household and institutional human recognition:

$$x_i = \alpha_i + \beta_i X + \varepsilon . x_i \qquad (7.1)$$

The measurement model for land use behaviour and community participation:

$$y_i = \alpha_i + \beta_i Y + \varepsilon . y_i \qquad (7.2)$$

Where x_i and y_i are vectors of endogenous and exogenous predictor variables, $i = 1, 2, 3, \cdots, n$, respectively, β measures the impact of the latent constructs while $\varepsilon . x_i$ and $\varepsilon . y_i$ are vectors of measurement errors in x and y. In our specification, it encompasses both observed variables used for the latent exogenous and endogenous constructs.

The structural component which measures the impact of the exogenous latent variable on the endogenous variable of interest is given as follows:

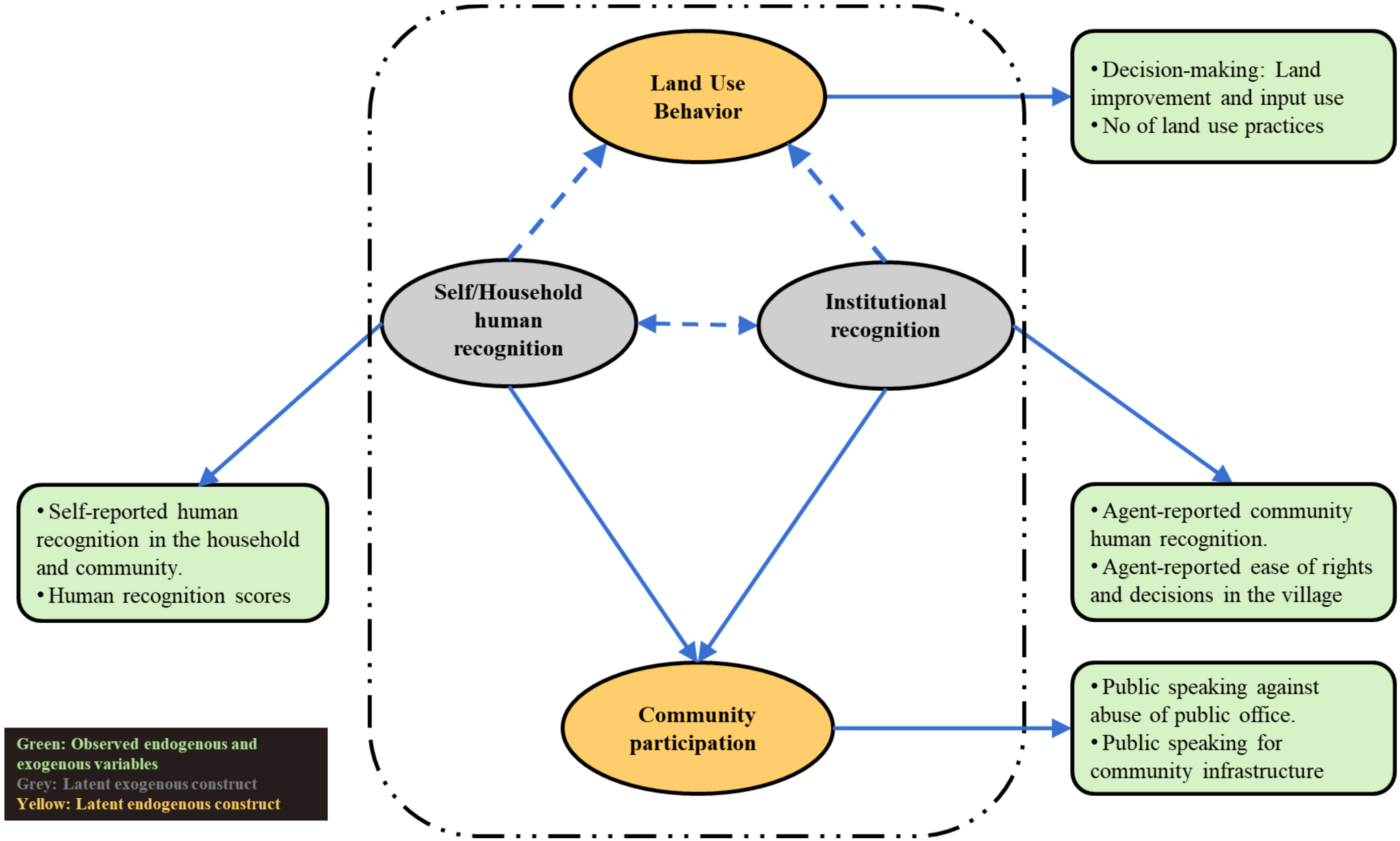
$$Y = \mathrm{B}Y + \Gamma X + \zeta \qquad (7.3)$$

Where Y measures the endogenous latent constructs of interest (land use behaviour and community participation), X is the exogenous latent constructs (self/household and institutional human recognition), B measures the relationship among the endogenous latent constructs, Γ measures the impact of the exogenous latent construct on the endogenous latent construct and ζ is the residual of Y.

Figure 7-1 illustrates the relationship between the latent human recognition and land use behaviour. The arrows show the directions of influence. First, the latent construct of self/household human recognition contains three variables: an additive score for self-reported human recognition received in the household, an additive score of self-reported human recognition received in the community and a measure of human recognition generated using the Alkire-Foster method on indicators or violence, humiliation, power and autonomy. Second, the latent construct of institutional recognition contains three observed variables. They are three additive scores community agent-reported recognition measures on a) ease of access to rights: property and divorce, b) ease of participating autonomously in binding village-level decisions and c) a measure of community recognition for general and female members. We constructed these institutional scores by taking the average response from the community agents by district surveyed. Finally, the latent endogenous construct for community participation contains two variables on public speaking capacities for a) comfortably speaking for redirection of public funds for developing community infrastructure and b) comfortably speaking out against abuse of public office.

Land use behaviour (LUB) is a latent construct that includes three variables capturing the behaviour towards land use in agriculture: two categorical measure of final decisionmaker for agricultural land improvement undertakings and agricultural input use and a sum total of responsible land use practices implemented in the last cropping cycle from the following list: Crop rotation, use of improved seed, use of irrigation technology, use of herbicides and pesticides as well as other forms of farm enhancements. We estimate the model using maximum likelihood estimation (ML) and report model estimates. We also use modification indices to include covariance matrices which are relevant to our model (available on request). We use multiple fit indices to evaluate whether our model was a good fit reporting the comparative fit index (CFI), the root mean squared error of approximation (RMSEA), and chi-square goodness-of-fit statistics. A satisfactory fit is indicated by CFI values greater than 0.95, nonsignificant chi-square (Hu & Bentler, 1998, pp. 424–453; Hu & Bentler, 1999, pp. 1–55) and RMSEA values less than 0.05 (Steiger, 1990, pp. 173–180).

Figure 7-1. Model of interaction: land use behaviour, human recognition and community discourse



Study Area Statistics

We conducted a farm household surveys in 2 districts in the central region and 3 districts in the southern region of Malawi: Lilongwe (7 communities), Salima (7 communities), Mangochi (8 communities), Chiradzulu (7 communities) and Nsanje (10 communities). The field work was done between May and July 2017. Data was collected from ca. 190 respondents per district yielding a total of ca. 950 respondents. We designed two questionnaires (community and household) to measure individual, household and community human recognition.

The study area also encompasses several climatic and agro-ecological zones with cooler seasons found in Lilongwe, Salima and Mangochi and hotter seasons in Chiradzulu and Nsanje. Rain-fed agriculture is predominant and raining season runs between November and March. These districts present different patterns in economic development and cultural institutions for women that influence breath of human recognition. Lilongwe and Mangochi are both predominantly matrilineal districts while Nsanje is a patrilineal district. Chiradzulu and Salima presents a mixture of both lineages. For the final analysis, we selected women farmers in households with agricultural land and whom reported crop and land improvements for the last cropping cycle, giving a total of 619 respondents.

Agriculture very important in Malawi (Asfaw et al., 2016, p. 645; Malley, Taeb, & Matsumoto, 2009, p. 176; Munthali & Murayama, 2013, p. 158). On average, most smallholder farmers farm on less than 1 hectare. Similar to Munthali and Murayama (2013, p. 160), we observe maize is the main crop cultivated in the surveyed regions followed by beans and peas as well as groundnuts. However, the number of land use practice implemented varied across first[48] crops. Similarly, the number of land use practices also varies across household heads and districts with household in Nsanje, a predominantly patrilineal area

[48] Each respondent reported the first three main crops cultivated in the last cropping cycle. 22% of the women farmers reported they cultivated for one crop type, 41% for 2 different crop types and only 34% for 3 different crop types.

implementing less practices overall. Just like Waldman et al. (2016, p. 1088), we treat the relationship between human recognition and land use behaviour as distinct to women farmers in communities in these districts.

Community descriptive statistics

The community questionnaire collected information from about 60 community agents in the 5-surveyed districts. The community agents ranged from village heads, the headmasters and mistresses, the healthcare workers, the police, agricultural extension workers etc., and consists of even distribution for both genders to avoid bias. Years of residency collected for community agents also show that they have lived in the community for a reasonable time (more than 5 years) and thus, are most likely to be knowledgeable about the human recognition provision for women farmers, the challenges and their favourability towards adopting certain land use behaviour and community participation. Table 7-1 shows the descriptive statistics of measurement variables and their corresponding latent construct.

Table 7-1 Descriptive summary of measurement variables

Measurement variables	No of variables	Equation name	Mean	Type
Land use behaviour		LUB		
Number of land use practices employed in the last croping cycle	5	No of land use practies	1.407	Count (0-5)
Decision-maker: Agricultural land Improvements	1	Deci: Land improv	2.984	Categorical (1-4)
Decision-maker: Agricultural input use	1	Deci: Input use	2.986	Categorical (1-4)
Self/household human recognition(SR)		Recog:S/HH		
Human recognition scores		MDI:HR	7.295	Continous
Subjective human recognition (Self)	3	SR: Subj. Self HR	9.386	Likert (1-4)
Subjective human recognition (Community)	3	SR: Subj.Comm. HR	9.313	Likert (1-4)
Community human recognition(AR)		Insti		
Ease of partaking in village decision	3	AR: Ease decision	2.444	Likert (1-4)
Ease of property rights and divorce	3	AR: Ease rights	2.743	Likert (1-4)
General and female community recognition	9	AR: G&F Comm.HR	14.383	Likert (1-4)
Participation in community discourse		Par_comm		
Comfort for public speaking: misbehaviour of public officials	1	PS: Misbehaviour	2.94	Likert (1-5)
Comfort for public speaking: community infrastructure	1	PS:Infra	3.094	Likert (1-5)

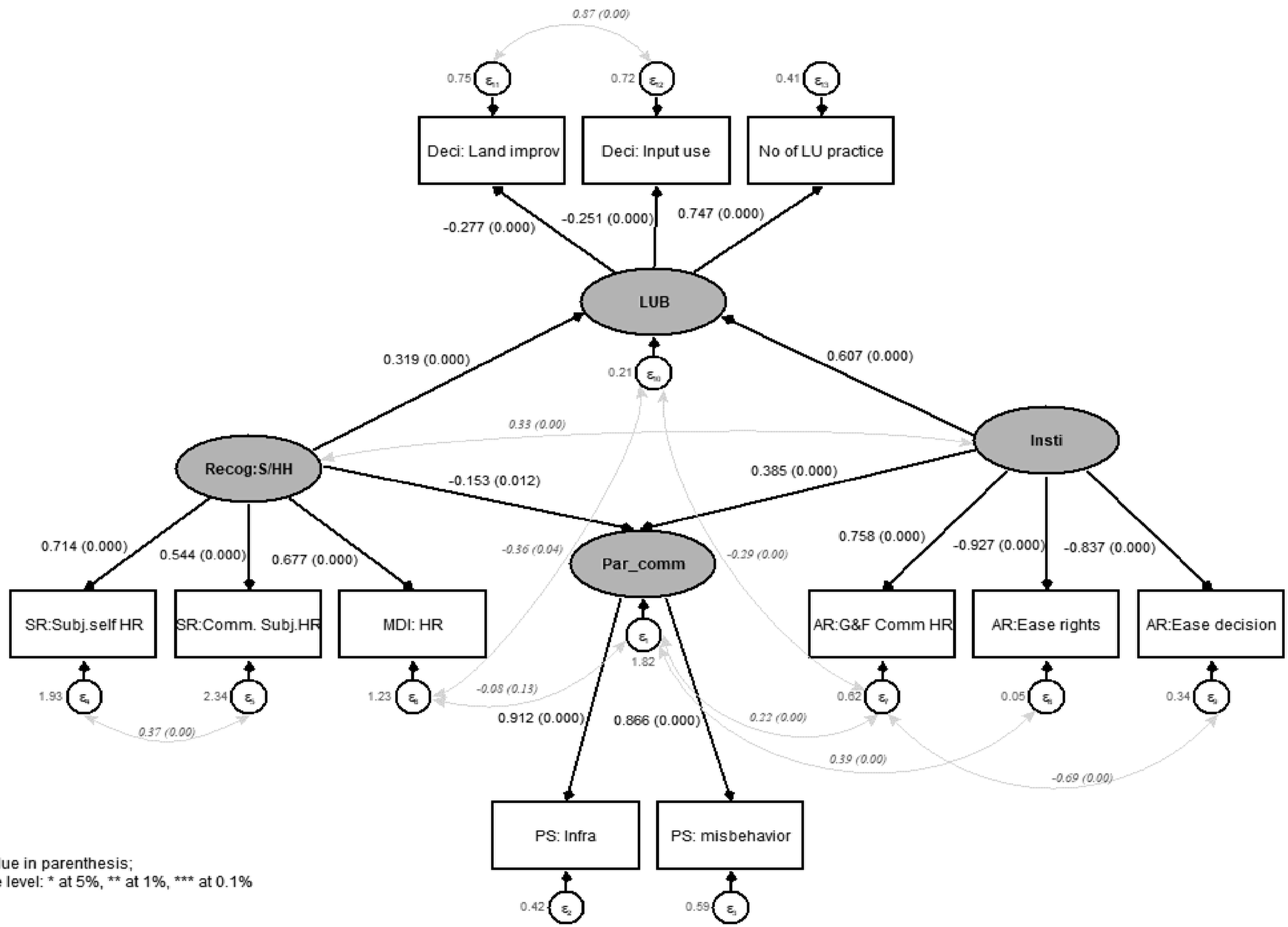
Notes: AR=Agent reported: SR=Self reported

On average, 1 land use practice was implemented by a woman farmer in the last cropping cycle. About 37% of women farmers reported that they were the final decision maker for input use in the household compared to 23% that reported spouse/partner and 38% that reported joint decision-making. About 38% of our respondents reported that they make the final decision on land improvements compared to spouse sole decision at 23% and household joint decision at 37%. Only 1% reported that someone else is the decision maker for land improvement. Finally, 27% reported discomfort in speaking for community infrastructure, 26% reported fair comfort while 25% reported very comfortable. Ca.78% of our respondents are between 18-48 years old, 39% have no education at all while 9% has education between secondary level 1-6.

Results: Self/household and Institutional Human Recognition on Land Use Behaviour and Community Participation.

Figure 7-2 and Table 7-2 shows the estimated results. We comment only on the standardized beta coefficients. We set the normalization constraints i.e., anchor point, for self/household and institutional human recognition at the indicators for number of land use practices implemented and agent-reported general/female community recognition respectively. The path coefficients in the model suggests strong relationship between observed variables and the latent construct. Self/household and institutional human recognition significantly affects women farmer's land use behaviours and community participation. The beta path coefficients for self/household human recognition and institutional recognition influence on land use behaviour(LUB) are 0.319 (p=000) and 0.607 (p=000) respectively. That is self/household human recognition and community human recognition increases land use behaviour by 32% and 61% respectively. Thus, women farmers in communities with better self/household human recognition and institutional recognition are likely to take on land use behaviour to improve their farmlands. Interestingly we see that land use behaviour has a negative influence (-27% and -25%) on decisionmaker for land improvement and input use i.e., the land manager. That is, land use behaviour to improve farm lands decreases the chances that the final decision maker is the woman farmer alone. We also note that self/household human recognition significantly reduces community participation by 15% while institutional recognition significantly and positively impacts community participation by 39%.

Figure 7-2. Pathway of human recognition on land use behaviour and community participation



Notes: P-value in parenthesis;
Significance level: * at 5%, ** at 1%, *** at 0.1%

Drivers of self/household human recognition (Recog:S/HH)

All three variables, i.e., self-reported subjective self and community human recognition as well as Alkire-Foster method-measured positive human recognition are positive and significantly influenced by self/household human recognition. Self-reported subjective self and community human recognition are 71% and 54% influenced by self/household human recognition respectively. Alkire foster-measured positive human recognition is 68% positively and significant influenced by self/household human recognition.

Drivers of institutional recognition (Insti)

Institutional recognition has a positive and significant influence on agent reported general and female community recognition by 76% in these communities. In contrast to self/HH human recognition, agent-reported ease of village decision participation and ease of rights are negatively and significantly influenced by institutional recognition. Particularly, institutional recognition influence on ease of rights and participation in binding village decisions are -93% and -84% respectively. It is imperative to examine all three variables side by side. Although community agents report that community members including women, are recognized within their communities, the institutional frame in place do not support easy access to rights in property and divorce and participation in binding village decisions. This gives us a glimpse on how underlying structural challenges like norms affect women and do not allow them the full exercise of rights as community members. It also shows the discrepancy between community perception of how women are treated and valued and the institutions in place that determines the rights to assets and decision-making.

Table 7-2 Effects of human recognition on land use behaviour and community participation

Structural equations		coefficient	Standardized beta
Land use behaviour (LUB) ←			
	Insti (LV)	0.166***	0.607***
		{0.033}	(0.066)
	Recog:S/HH (LV)	0.056**	0.319**
		{0.020}	(0.083)
Par_comm←			
	Insti (LV)	0.612***	0.385***
		{0.093}	(0.053)
	Recog:S/HH (LV)	-0.156*	-0.153*
Measurement		{0.066}	(0.061)
Deci: Land improv←			
	LUB(LV)	-0.344***	-0.277***
		{0.066}	(0.045)
Deci: Input use←			
	LUB(LV)	-0.306***	-0.251***
		{0.064}	(0.045)
No of land use practices←			
	LUB(LV)	1.000***	0.747***
		{.}	(0.069)
AR:G&F Comm. HR←			
	Insti (LV)	1.000***	0.758***
		{.}	(0.027)
AR: Ease decision←			
	Insti (LV)	-0.973***	-0.837***
		{0.027}	(0.023)
AR:Ease rights←			
	Insti (LV)	-0.635***	-0.927***
		{0.039}	(0.022)
SR: Subj.self HR←			
	Recog:S/HH (LV)	1.000	0.714***
		{.}	(0.068)
SR: Subj.comm HR←			
	Recog:S/HH (LV)	0.699***	0.544***
		{0.057}	(0.059)
MDI: HR←			
	Recog:S/HH (LV)	0.721***	0.677***
		{0.134}	(0.065)
PS: Misbehaviour←			
	Par_comm (LV)	0.919***	0.866***
		{0.061}	(0.028)
PS: Infra←			
	Par_comm (LV)	1.000***	0.912***
		{.}	(0.028)
Observations		619	619

Note: Point estimate standard error in curly parenthesis {}; Standardized beta coefficient standard error in parenthesis (); LV= Latent Variable; Significance level: * at 5%, ** at 1%, *** at 0.1%

Model fit: We assess our model goodness of fit by estimating goodness of fit indices. SEM method provides a variety of indicators to verify the degree to which the hypothesized model is close to the estimated sample. Table 7-3 highlights the model fit for influencing factors for land use behaviour. These fit indices are used to check model adequacy: the Chi-square test, the comparative fit index (CFI), the standardized root mean square residual (SRMR) and the root mean square error of approximation (RMSEA) (Hu & Bentler, 1998, pp. 424–453; Hu & Bentler, 1999, pp. 1–55). The CFI index shows how well the hypothesis model fits with the non-nested model. The null hypothesis of the Chi-square tests that the observed and estimated covariance matrices in the model are unbiased.

Table 7-3 Model goodness of fit

Fit index		Value	Criterion	Implication
Likelihood ratio	Chi ^{2}	43.722 p=0.064	Non-significant (p>0.05)	Model is a good fit
Population error				
Root mean squared error of approximation	RMSEA	0.026	<0.05	Acceptable
Baseline comparison				
Tucker Lewis index	TLI	0.994	>0.90	Acceptable
Comparative fit index	CFI	0.997	>0.90	Acceptable
Size of residuals				
Coefficient of determination	CD	0.979	>0.90	Acceptable
Standardized root mean squared residuals	SRMR	0.026	<0.05	Acceptable

Notes: See Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-12 for equation level goodness of fit

A non-significant Chi-square test ($p > 0.05$) signifies that the data provided a good fit to the model. CFI index is normally accepted at a value of at least 0.9 to indicate the model fit. The SRMR describes the differences between the observed and predicted covariance and accepts a model fit within the threshold of SRMR < 0.05. The RMSEA measures the amount of variation between the observed covariance matrix and the hypothesized covariance matrix. Table 7-3 shows that overall model fit for factors influencing land use behaviour are acceptable.

We also assess the convergent and discriminant validity of our measurement variables. Convergent or construct validity argues that the indicators chosen to measure the latent construct should interact in a such a way that captures the latent essence of the construct while discriminant validity measures the extent to which measures of different latent construct are distinct (Bagozzi, Yi, & Phillips, 1991, p. 425; Li, Wei, Zhu, & Guo, 2019, p. 8; Zait & Bertea, 2011, p. 217). Squared correlation matrix and averaged variance extracted (AVE) can be used to assess both convergent and discriminant validity. A latent construct must meet the following criteria to satisfy the appropriate degree of convergent and discriminant validity: the average extracted variance should be greater than 0.5 for convergent validity and less than the values of the squared correlations among latent constructs for discriminant validity as show in Table 7-4. As seen from the table, the criteria are satisfied indicating that measurement model has a good discriminant and convergent validity.

Table 7-4 Test for Discriminant and convergent validity

Squared correlations (SC) among latent variables				
	LUB	Insti	Recog:S/HH	Par_comm
LUB	1			
Insti	0.018	1		
Recog: S/HH	0.048	0.065	1	
Par_comm	0.003	0.088	0	1
Average variance extracted (AVE) by latent variables				
Latent variable	AVE		Convergent validity	Discriminant validity
AVE_LUB	0.602		Acceptable	Acceptable
AVE_Insti	0.798		Acceptable	Acceptable
AVE_Recog:S/HH	0.520		Acceptable	Acceptable
AVE_Par_comm	0.795		Acceptable	Acceptable

Notes: when AVE values >=SC values there is no problem with discriminant validity
when AVE values >= 0.5 there is no problem with convergent validity

Indirect impact of self/household and community recognition

Table 7-5 presents the indirect effects of self/household and institutional recognition on indicators of land use behaviour and community participation.

Particularly, self/household and institutional recognition has an indirect and negative influence on who the decisionmaker for farm land improvement is by 6% and 17% respectively. Better human recognition at the household and institutional level increases the chance that the final decisionmaker in the household for farm land improvement and input use is not the woman farmer alone. One may argue that it also increases the chance that such decisions are made by the household jointly.

Table 7-5 Indirect effects of human recognition on indicators of land use behaviour and community participation

Structural equations		Indirect effects
Deci: Land Improv←		Coefficient
	Recog:S/HH (LV)	-0.056**
		(0.020)
	Insti (LV)	-0.166***
		(0.033)
Deci: Input use←		
	Recog:S/HH (LV)	-0.050**
		(0.019)
	Insti (LV)	-0.148***
		(0.031)
No of land use practices ←		
	Recog:S/HH (LV)	0.163***
		(0.048)
	Insti (LV)	0.482***
		(0.051)
PS: Infra←		
	Recog:S/HH (LV)	-0.157*
		(0.066)
	Insti (LV)	0.612***
		(0.093)
PS: Misbehaviour←		
	Recog:S/HH (LV)	-0.144*
		(0.061)
	Insti (LV)	0.562***
		(0.086)

Note: Standardized beta coefficient standard error in parenthesis (); errors (LV)= Latent Variable; Significance level: * at 5%, ** at 1%, *** at 0.1%

As expected, self/household and institutional recognition has a positively and indirect influence on the number of land use practices implemented. That is, women with better self/household and communities with institutional recognition indirectly increases the number of land use practices implemented on the farm by 16% and 48% respectively. This means that land use practices to improve farm lands can be indirectly supported by self/household and institutional recognition if barriers that hinder women as recognized economic agents are removed or reconciled.

Finally, institutional recognition has an indirect and positive influence on public speaking for community infrastructure and public office abuse (61% and 52%) while self/household human recognition has an indirect and negative influence on community participation.

Discussion

Using structural equation modelling (SEM), we examine the influence of human recognition on land use behaviour and community participation for women farmers in communities in 5 Malawian districts.

First, self/household human recognition and institutional recognition has a positive influence on land use behaviour. Delving into the indicators of institutional recognition show that better agent-reported community recognition does not result in better overall ease of village decision-making and rights. This consistent with World Bank (2006, pp. 18–30) and (Lovo, 2016, p. 219) which argues that women's status in their community viewed through the lens of rights, is one challenge facing adoption of improved land use with effects on short and long-term conservation investments.

Second, we note that improved land use behaviour is mostly adopted when the woman farmer does not make the final decision on input use and land improvements i.e., does not manage the land. One path of influence could be through gendered decision-making allocation in traditional agricultural households where decision-making for farm land management(e.g., what and how to grow) may be seen as a predominately male domain or carried out jointly in the household regardless of tenure system as observed by Kishindo (2010, pp. 94–95) and Djurfeldt et al. (2018, p. 606). This in line with our findings.

One cannot also ignore the effect of managerial capabilities of the woman farmer. Traditional roles in Malawi may see woman farmers as lacking the know-how to make land decisions and thus, may leave the domain solely to their spouse or make the decision jointly. For female headed household, financial or labour capabilities may be particularly constrained as argued by Toma et al. (2018, p. 864), Waldman et al. (2016, p. 1094) and Meinzen-Dick et al. (1997, p. 1312). Most land use practices are expensive and involves investments which may not yield immediate returns as noted by Lovo (2016, p. 226). Trade-off may also exist between household short-term nutritional security and long-term land improvement outlook as most rural household only want to have enough food until the next cropping cycle.

Finally, we observe that institutional recognition directly improves participation in community participation for women farmers. That is, women farmers with better institutional recognition feel more comfortable speaking out on community issues. This is supported by Castleman (2016, p. 142) who argues practices that improve individual's human recognition within the community may contribute significantly to improving community voice, accountability and participation.

Our results are consistent with expectation that positive human recognition influences land use behaviour and community participation positively. We note that overall, women farmers with better recognition are more likely to participate in the community and to implement land use behaviour. We also not that they are less likely to the ones to take decision on the final farm land improvement ventures. The latter could also signal the discrepancy between who makes the decision to implement and actual implementation.

Conclusion

We examine the influence of human recognition on land use behaviour and community participation for women farmers in 5 Malawian districts. We find that self/household human and institutional recognition has a positive influence on land use behaviour and community participation.

Our findings have interesting policy implications. Firstly, human recognition has significant influence overall land management should not be ruled out when discussing land use management issues in community discourse. Improved land use behaviour significantly influences who makes decisions on land improvements and input use. Thus, if certain land use behaviour is to be adopted in these communities, future reforms should reconcile the gap between farmland owners and farm managers. As argued by Lovo (2016, p. 228), this is important as ownership and management rights still remain separate rights in Malawi. Second, the effect of institutional recognition cannot be overstated. The dependence of land use behaviour on how community members are viewed as productive agents and value adders in their society is a very important intersection which has not been analysed before. Thus, structural policies should tackle obstacles facing women in the community and improve the perception of women farmers as drivers of responsible land use management. Finally, further research to investigate the exact mechanism and pathway of human recognition on overall land management is urgently needed.

8. Conclusion

Gender inequality in access to and control of productive resources and socioeconomic welfare heavily impacts human recognition for women sub-Saharan Africa. It dictates how women are viewed, valued and treated with significant effect on poverty and household wellbeing especially in Malawi. To this end, this thesis investigates the impact of human recognition on wellbeing for women farmers in Malawi. The contributions examine and report results from five research objectives in chapters 3-7. It also highlights the current problem facing women farmers and resource access in sub-Saharan Africa and links development outcomes to the missing dimensions of poverty, which includes human recognition. Furthermore, the model of human recognition reception for women farmers highlights the direct and indirect impact human recognition has on land access and other wellbeing factors (see chapter 1 and 2).

Beyond the introduction and theoretical model, the contributions in this thesis:

1) assesses the indicators of multidimensional (negative) human recognition (deprivation) with the domains of interaction for women: self, household, community/institution and develops an index of multidimensional (negative) human recognition (deprivation) with various measurement parameters (chapter 3).
2) investigates the determinants of human recognition deprivation for women with a comparative analysis of Malawi and Peru (chapter 4).
3) examines the effect of negative human recognition on land access and household wellbeing for women farmers in Malawi using size of household agricultural landholding and child nutritional diversity as proxies respectively (chapter 5).
4) outline a multilevel sampling approach for development survey data collection for developing country context. (chapter 6) and finally,
5) examines the effect of self, household and institutional human recognition on responsible land management and land use choices for Malawian women farmers using primary data from a field survey (chapter 7).

The sections below address the findings from the various contributions in line with the research objectives and hypothesis from chapter 2.

Research objective 1 with research hypotheses (1):

In line with Heise et al. (1994, p. 1165), violence against women indeed relates to women as a group within the society and are also negative human recognition manifestations. These manifestations are not only present on individual and household level but appear as structural and institutional forms of discrimination which women experience as class. Therefore, indicators of violence, humiliation, dehumanization and autonomy with regards to their sources within three domains, namely the self, household, and community domains, according to Castleman (2012, pp. 35–36) as better representations of negative human recognition transactions with women experience.

Thus, using these indicators with their domain of interaction, paper 1 (chapter 3) successfully presents various measures of human recognition deprivation, employing the Alkire Foster method to calculate the Human recognition Deprivation Index (HRDI), the deprivation headcount ratio and intensity for women in Malawi. Overall, up to 16% of women in Malawi are human recognition deprived in one domain with deprivation intensity of 43%. 17.5% of women working in agriculture (women farmers) are deprived with a deprivation intensity of up to 43%. Finally, there is a higher human recognition deprivation for women in northern Malawi compared to women other regions due to the patrilineal and matrilineal structures present in the various regions (Conroy, 2014, p. 869). These findings provide successful answers to research hypotheses 1(a), (b) and (c) for paper 1 (chapter 3) in this thesis

Research objective 2 with research hypotheses (2):

In line with (Grabe et al., 2015, p. 8), indeed, complex, dynamic interactions of power influence women bargaining in different social domains. Because violence and deprivation are embedded in institutional structures and cultural practices present in where individuals interact, negative institutions like patriarchy inflict violence over time by justifying direct violence (visible) and legitimizing institutional violence (invisible), with significant impact negative human recognition. Furthermore, studies on factors influencing women's vulnerability to disempowerment, institutional and partner violence fail to link certain social-demographic and socioeconomic factors to negative human recognition in developing countries. To this end, paper 2 (chapter 4) calculates the negative human recognition scores for women in Malawi and Peru and establish a dichotomous censored count of deprived women (1 = deprived, 0 = otherwise). Using the censored count as the dependent variable, it extracts the associations between social demographic and socioeconomic factors using logistic regression for women in both countries. Overall, educated spouses/partners and women are less likely to provide or receive negative human recognition respectively. Finally, women are likely to be deprived if they were married more than once, have alcoholic partner/spouses and exert retaliatory behaviour. Additional heterogeneous outcomes exist for women farmers, underlined by cultural differences in both countries. Analysing poverty and women recognition deprivation profiles, it suggests that women with little education are likely to be farmers in Malawi and likely to be poor in Peru, thus likely to be human recognition deprived in both countries. The findings from paper 2 (chapter 4) provides support for research objective 2 with successful investigation of research hypotheses 2(a) and (b). However, it also shows research hypothesis 2(c) to be partially fulfilled i.e., social-demographic and socioeconomic factors of human recognition deprivations are consistent in some determinants (education, multiple marriages, alcoholic partners etc.) and varies across others (women working in agriculture) across Malawi and Peru.

Research objective 3 with research hypotheses (3):

Similar to Kodoth (2001, pp. 291–292), gendered patterns of agency, including bargaining power for land access does influence women's positions in social institutions like household, community, and ethnic group. As a result, the feminist theory of intra-household economics perspective recognizes household members as gendered individuals. This means that for women, resource allocation in households are power pay-off determined by a series of bargaining positions with exit options in the case of a negotiation breakdown (Katz, 1997, p. 26). In non-cooperative households with non-viable exit options, provision of negative human recognition is one way of keeping limited resource in line with principal (partner) preferences. To this effect, contribution/paper 3 (chapter 5) outlines a simple non-cooperative, principal-agent bargaining model of land access and negative human recognition provision for women farmers in Malawi in the absence of viable exit options. The results from the OLS and IV regressions, show that negative human recognition has positive and significant impact on household land access for women farmers overall and for matrilineal women farmers. However, negative human recognition is significantly and negatively correlated with household wellbeing proxied by household child dietary diversity.

The findings from this contribution provides support for research hypotheses 3(a) and also supports human recognition model equation (2.11) from chapter 2, that is, human recognition's influence on land access is greater than zero. Interestingly, in a non-cooperative household bargaining model with little or no viable exit options, a larger agricultural landholding and thus, land access is not accompanied by a monotonous decrease in negative human recognition provided. Negative human recognition reception is one of the prices women pay to access land in rural Malawi. The findings from this contribution also provides support for research hypotheses 3(b) and human recognition model equations (2.12 and 2.13) from chapter 2. That is negative (positive) human recognition has a significant direct and indirect effect on household nutritional wellbeing of a woman farmer.

Research objective 4 with research hypotheses (4):

Vital to development studies is the ability to investigate the prevalence of certain development factors in a target population. One tool for achieving these aims is the use of spatial and systematic random sampling in multistage survey designs. Spatial sampling is essential to development research because researchers use spatial information to examine socioeconomic conditions of a target population (Kondo et al., 2014, p. 1; Vanden Eng et al., 2007). As researchers cannot sample every household or individuals in most studies, sampling methods that generate relevant data is paramount to developing meaningful estimates from target population sample (Armoogum & Dill, 2015; Kondo et al., 2014). Sampling difficulties are prevalent in resource-constrained settings where it is hard to obtain accurate and up-to-date data (Kondo et al., 2014). As a result, paper 4 (chapter 6) of this thesis presents multilevel sampling approach for use in areas where comprehensive information on geographical or household characteristics is not available. This approach uses geographical information systems (GIS) for random spatial sampling, and personal digital assistants (PDAs) with global positioning system (GPS) for the household systematic random sampling with random walk. Using descriptive comparison of human recognition, the study shows that negative human recognition values derived from the 2017 survey data fall within a comparable range of the Malawi DHS data, which is nationally representative. However, the study also presents the limitations of the sampling approach in form of field interviewer's bias or measurement errors and recommend further testing in developing country context. The findings from this contribution provide successful answers to research objective and hypotheses 4(a) outline in chapter 2.

Research objective 5 with research hypotheses (5):

In the context of responsible land management, inter, intrapersonal relationship and land decision dynamics in households are pertinent in the overall evaluation of land interventions (deVries & Chigbu, 2017, pp. 65–73). Paper 5 (chapter 7) investigates and outlines the findings on the effect of self, household and institutional human recognition on responsible land management and land use choices for Malawian women farmers. Using structural equation modelling, it examines the extent to which self/household and institutional human recognition in the community influences certain land use behaviour and participation in community discourse. Overall, the findings show that, first, self/household human recognition and institutional recognition has a positive influence on responsible land use choices i.e., responsible land use behaviour. Second, institutional recognition has a significant positive effect on participation in community discourse for women farmers. That is, women farmers with better institutional recognition feel more comfortable speaking out on community issues. However, the study also finds that responsible land use choices is mostly adopted when the woman farmer is not the final decision maker on input use and land improvements due to the observation that decision-making for farm land management(e.g., what and how to grow) are seen as a predominately male domain in traditional agrarian households, in line with Kishindo (2010, pp. 94–95) and Djurfeldt et al. (2018, p. 606). The findings from this contribution provide successful answers to research objective and hypotheses 5(a) and (b).

9. Recommendations

Evidence from the various contributions show the significant impact of human recognition on resource access such as land and wellbeing of women farmers in Malawi.

First, human recognition deprivation index for women and women farmers were successfully indicators of humiliation, dehumanization, violence, and lack of autonomy within the domains of interaction for women. Using the Alkire Foster method, the thesis outlines the social demographic and socioeconomic determinants of human recognition deprivation for women. Further linking human recognition to women farmers' bargaining power and ability to access land resource, it shows the significant impact negative human recognition has on the wellbeing of women farmers in Malawi especially in the prevalent non-cooperative bargaining framework of agrarian households. Similar to Mishra and Sam (2016, p. 360), the findings show that women with positive human recognition are likely to participate in community projects and responsible land management; and are also likely to invest in human capital like child and household nutritional wellbeing. Examining secondary data side by side with primary data from Malawi as case study, this thesis shows that, indeed, positive human recognition has significant influence on responsible land use of women farmers like conservation practices as well as gives women farmers, better status in community discourse. It, however, notes relevant policy recommendations as follows:

For Policy makers and Administrators

<u>Recommendations from Paper 1 in chapter 3:</u>

In developing measures of intangible concepts of human development like human recognition, policy makers should keep in mind, constraints inherent in developing country context and consider methodological approach to human development data from poorer populations. For instance, Alkire and

Foster (2011, p. 483) argues that in measuring a multidimensional human development concept, different cut-offs values could be used to highlight and establish policy priorities. Important domains of interaction for women can be isolated and targeted by assigning different weights to the different target domains. Alternatively, policy makers can focus on multidimensionally deprived strata of the population by setting cut-off points to investigate groups with joint deprivations or highest intensities, for example. Budget-constrained analysis on policy sections like resource access like land can be carried out by slicing out a sub-population. Finally, the Alkire Foster methodology can be applied to measure other intangible concepts of development in other countries.

Recommendations from Paper 2 in chapter 4:

Once the human development measure is created, the next steps should include investigating the factors influencing the said measure in the general or target population. As established in paper 2 (chapter 4) with human recognition, certain social demographic and socioeconomic factors influences human recognition deprivation in Malawi and Peru. Two determinants namely, education and occupation as a woman farmer, remain consistently impactful in both countries. The study notes that these two determinants implicated in the human recognition deprivation profiles of women are also implicated in poverty studies of Mukherjee and Benson (2003, p. 339), Escobal (2001, p. 506) and Morley (2017, p. 20) in Malawi and Peru respectively. Given the agricultural dependency in both countries, women's level of human recognition can also affect their ability to access resources such as land within and outside their households as observed by Sraboni et al. (2014, p. 12). Therefore, educating women alone as a policy solution, will not be enough to reduce negative human recognition. Policy makers should improve all levels of education for both men and women, with impact on resource access like land and on poverty. Implementing other social policies/programs can improve women human recognition levels in combination with educational policies.

Recommendations from Paper 3 in chapter 5:

Isolating the target population for human development policies like equitable land resource access and other gender policies for women farmers require that a true empirical examination of the effect of such polices in the field. This encompasses determining the true nature of power dynamics and the under lying institutional and structural hindrances facing women farmers. Household dynamics are also important factors to consider by policy makers when rolling out interventions for overall wellbeing. As noted by Fafchamps (2001, pp. 68–96) and Malapit et al. (2015, pp. 1097–1120) wellbeing factors are credible threat point for women in making resource consumption choices in their households. Thus, policy makers should consider interventions that target women's household bargaining power and improve women's exit options as they would strengthen women farmers' household bargaining position. This should also be paired with enforceable rights to resource access like property right laws and access to legal and administrative recourse. In line with Mabsout and van Staveren (2010, pp. 783–794) and Wiig (2013, p. 105), policies to reverse gendered institutions and improving land ownership and access will improve wellbeing and human recognition levels. Policy improvement can be tailored to particularly targeting factors that support unequal power relations from the institutional and household perspective such as providing less costly recourse to dispute resolution, making and enforcing laws that protect women land rights and abolishing harmful cultural practices that strip women to autonomy.

<u>Recommendations from Paper 4 in chapter 7</u>

In addition to using secondary data, it is important that policy makers in the development sphere have the possibility of validating their findings by re-sampling a subset of the target population in the country of interest. Paper 4 show that this can be achieved in a developing country context using GPS, GIS and PDA technologies. Research data can be easily collated and analysed with speed and at lower cost. However, other challenges remain. Researchers and administrators preparing for field data collection should consider other factors when designing a multilevel PDA-based survey. Room for proper logistics planning, sufficient interview times, extensive training and briefing on fallback safety measures with regards to data backup should be included in the survey design. Avenues for measurement errors and sampling biases should be fully considers before embarking on field data collection. Finally, questionnaire design should be finished well in advance to facilitate enough time for extensive deployment and testing on PDAs.

Recommendations from Paper 5 in chapter 7:

Analysing Malawi primary data from women farmers shows that human recognition has significant influence overall responsible land management should not be ruled out in land use management issues and community discourse by administrators and policy makers. Since improved land use behaviour is significantly influenced by the final decision maker for land improvements and input use, future reforms on responsible hand use should reconcile the gap between farmland owners and farm managers, if responsible land use behaviour is to be adopted in these communities. This is important in Malawi where ownership and management rights still remain separate rights (Lovo, 2016, p. 228). Land administrators should examine, thoroughly, the dependence of land use behaviour on community members recognition as productive agents and value-adders in their society. This will create the basis on which policies that tackle obstacles facing women in the community and the perception of women farmers as drivers of responsible land use management could be further developed.

For Further Research

In addition to providing recommendations for policy, other relevant recommendations for further research are noted as follows:

Cross-sectional data used in this thesis, is limited in its analysis. Further research on human recognition deprivation and its impact on wellbeing and land as a resource for women farmers is better suited to panel data. Collecting panel data on human recognition levels of women over time can be a useful tool for policy makers in evaluating the efficacy of human recognition interventions.

Further analysis on the different domains of human recognition transactions is relevant to isolate the extensive contribution or dynamics of each domain and indicator to overall human recognition in Malawi and Peru. Better and disaggregated measures of land access and wellbeing is urgently need if researchers wish to extensively isolate and capture the dynamics of negative human recognition and wellbeing effect like land access or nutrition for women farmers within the non-cooperative framework of household bargaining.

Verifying secondary empirical results with primary data is pertinent for robust research. Therefore, further field survey to collect relevant data is always needed. As advances in GIS, GPS and PDA are becoming globally accepted and are simplifying the collection and analysis of development survey data, the new sampling approaches as proposed in this thesis can be further tested and validated with other methods to establish its usefulness for survey applications.

Finally, the development of responsible land management requires a proper understanding of how inter-personal relations affect land use choices. It also includes additional discourses on responsible land management and land governance in multi-disciplinary framework. Thus, further research in the domain of responsible land management can incorporate the human recognition as a facet of human development. Particularly, further investigation into the exact mechanism and pathway of human recognition impact on overall land management is urgently needed.

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A. Appendix and Supplementary Materials

Chapter 4 - Appendix: Estimating Human Recognition Deprivation

The multidimensional **h**uman **r**ecognition **d**eprivation **i**ndex – **HRDI** – is based on two components, the deprivation headcount ratio, H, and the deprivation intensity, A, as shown below (Alkire & Foster, 2011, p. 477):

$$HRDI = H \times A$$ (**Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-1)

Where

$$H(y;z) = \frac{q}{n} \quad \text{(A-2)}$$

is the total number of deprived individuals, *q*, divided by the total population, *n*.

The total number of deprived individuals, *q*, is given by:

$$q = q(y;z) = \sum_{i=1}^{n} \rho_k (y_i ; z_j) \quad \text{(A-3)}$$

where q is identified by mapping the individual i achievement vector, $\rho_k (y_i ; z_j)$, and y_i shows the individuals' $i = 1, 2, 3 \cdots, n$ achievement in j domains. Each domain $j = 1, 2, 3, \cdots, d$ is represented by a row of vectors showing domain-specific thresholds, z, with $z_j > 0$ and z_j as the first threshold below which individuals are classified as deprived in domain j. The identification parameter ρ_k captures deprived individuals using their achievement vector, y_i, and the deprivation cut-off, *k* as shown below. Let the matrix of achievement $n \times d$ of individuals $i = 1, 2, 3 \cdots, n$ in the domains of interaction from $j = 1, 2, 3, \cdots, d$ be:

$$\begin{bmatrix} y_{ij} & \cdots & y_{nj} \\ \vdots & \ddots & \vdots \\ y_{id} & \cdots & y_{nd} \end{bmatrix} \geq 0. \tag{A-4}$$

The row vector y_i shows the individual's achievement while the column vector y_{*j} gives the distribution of the j domain achievement across individuals. The first threshold, z_j identifies individuals deprived in the domain j. The second threshold identifies the deprivation cut-off, *k*, by counting the number domains required for individuals to be considered deprived in multiple domains.

The headcount ratio is adjusted by the deprivation intensity, A ,to calculate the final index (Alkire & Foster, 2011, pp. 477–480) as shown in equation (1) above. Deprivation intensity, A, is illustrated as:

$$A = \frac{|c_i(k)|}{qd} \tag{A-5}$$

and describes the fraction of possible domains in which average deprived individuals are deprived in (Alkire & Foster, 2011, pp. 476–479). The deprivation censored count, c_i, of individuals, *i*, is a dichotomous variable that takes the value of 1 when the deprivation score $c_i(k)$ is greater than or equal to the deprivation cut-off, k and 0 if otherwise. Composite index of aggregate human recognition, $\bar{r}$, is derived from equations (1-5) as follows:

$$\bar{r} \equiv HRDI = H \times A = \left(\frac{q}{n}\right) \times A \equiv \left(\frac{\sum_{i=1}^{n} w_i \rho_k(y_i, z_j)}{n}\right) \times \left(\frac{w_i\,|c_i(k)|}{qd}\right) \tag{A-6}$$

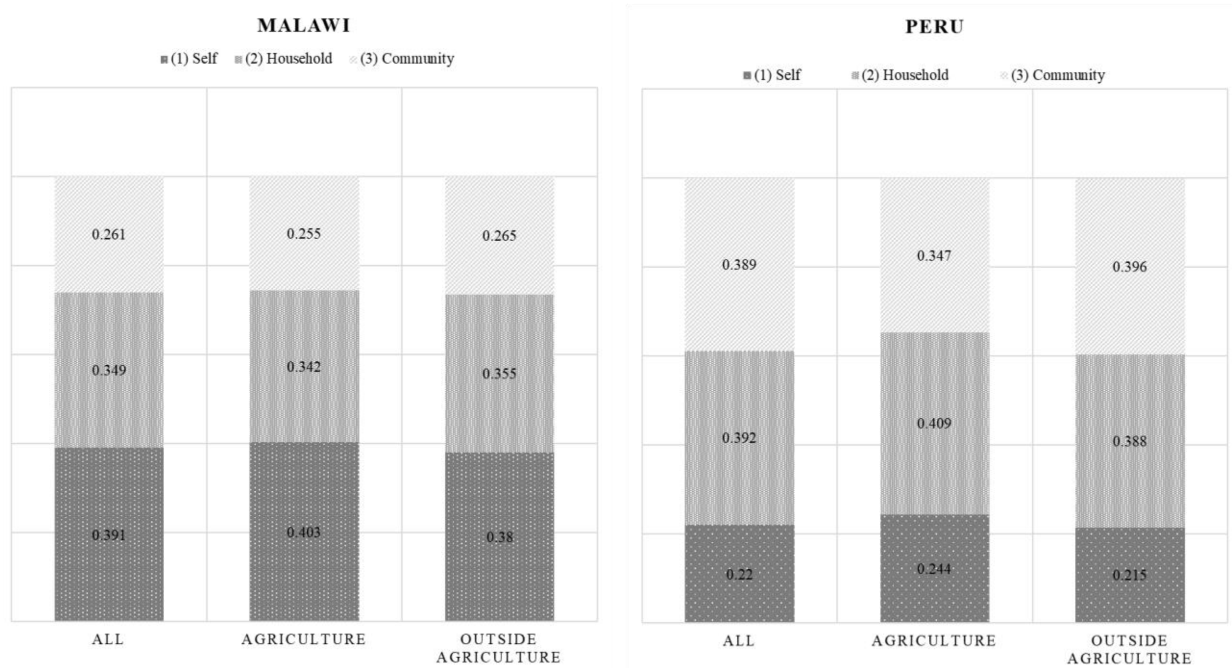
Where $\sum_{i=1}^{n} w_i \rho_k(y_i, z_j)$ is the weighted sum of individuals identified as deprived and $w_i\,|c_i(k)|$ denotes the weighted sum of possible recognition deprivation accruing to deprived individuals, *i*. Defining the HRDI on averages implicitly assigns equal weighting, $w_i = \frac{1}{j \cdots d}$ to each domain, j, where $j \cdots d$ is the total number of domains assessed. Alkire and Foster (2011, pp. 477–480) argue its ideal when all domains have equal impact. For alternative weighting structures, see Alkire and Foster (2011, pp. 477–480).

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.-**1 Chapter 4-Domains of human recognition deprivation and indicators

Domain	Source of human recognition	Domain indicators
Self (1)	Degree of autonomy in decisions pertaining exclusively to self.	Person with …
		- Usually decides on respondent's health care.
		- Usually decides on visits to respondent's family/relatives.
		- Usually decides on household purchases.
	Mental perception of violence.	Beating justified if … - wife goes out without telling spouse/partner
		- wife neglects children
		- wife goes argues with spouse/partner
		- wife refuses to have sex with spouse/partner
		- wife burns food
Household (2)	Interaction within the household regarding of freedom and self-determination.	Spouse/partner… - jealous if respondent talks with other men
		- accuses respondent of unfaithfulness
		- doesn't permit respondent to meet with female friends
		- tries to limit respondent's contact with family
		- insists on knowing where respondent is
	Incidence of violence.	Respondent has been… - humiliated, threatened with harm, insulted or made to feel bad by spouse/partner.
		- pushed, shook, had something thrown at, slapped, punched with a fist or hit by something harmful, had arm twisted or hair pulled by spouse/partner.
		- kicked or dragged, strangled or burnt, threatened with knife/gun or another weapon by spouse/partner.
		- physically forced into an unwanted sexual act or forced into another unwanted sexual act by spouse/partner.
		- physically forced to perform sexual acts respondent didn't want to.
		- bruises, eye injuries, sprains, dislocations or burns because of spouse/partner actions - hurt spouse/partner during a pregnancy.
Community (3)	Interactions with in the community.	Someone else … - physically hurt respondent in the community.
		- respondent during pregnancy in the community.

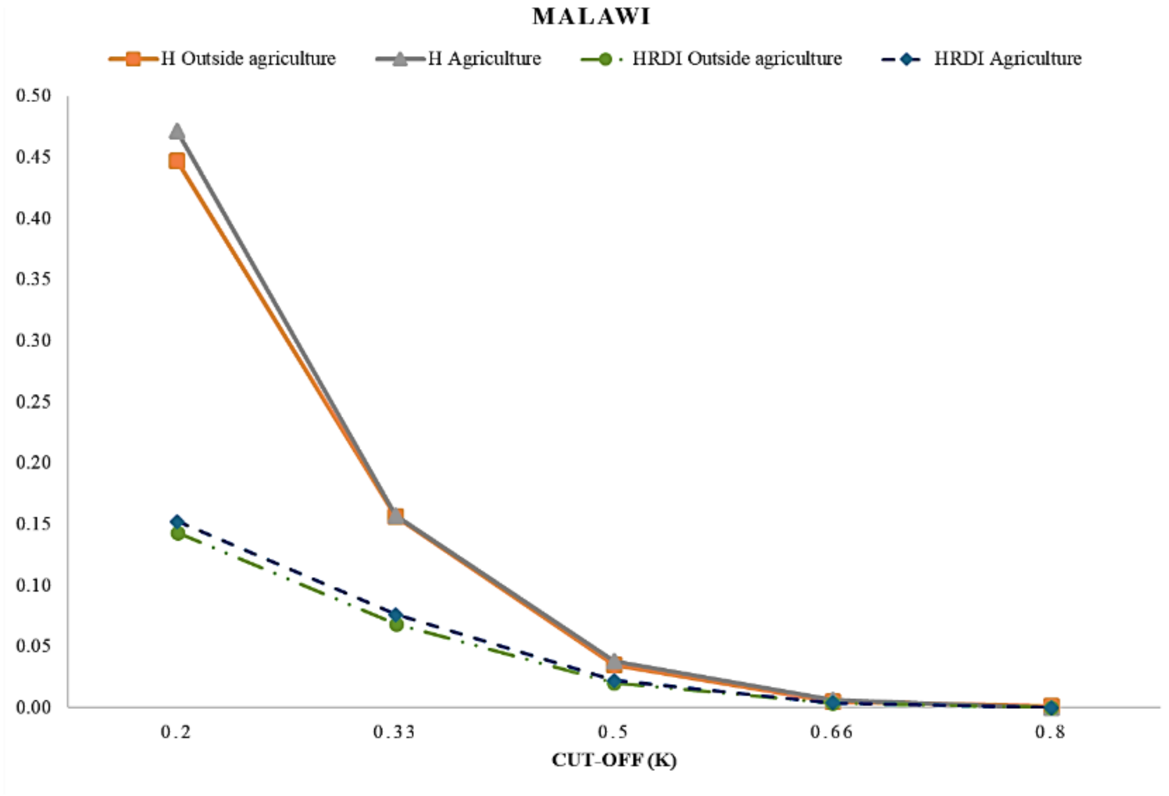
Source: Malawi and Peru Demographic and Health survey. Note: see footnote 15 for the rationale supporting self domain indicators.

Figure **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.-**1 Chapter 4-Contribution of each domain to the human recognition deprivation index (HRDI) for Malawi and Peru: By total population, women in agriculture and women outside agriculture.



Note: Cut-off point (k) = 33% (1/3)

Figure **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-2 Chapter 4-Deprivation headcount ratio (H) and HRDI dominance for women outside



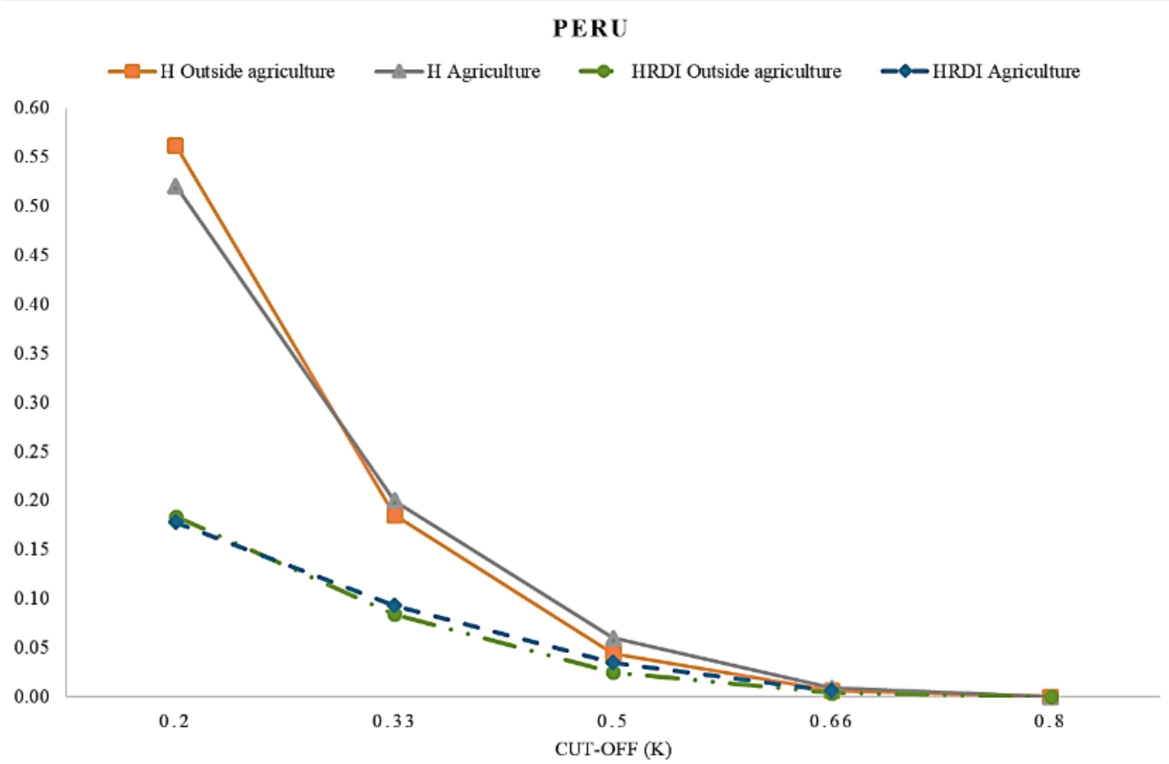


Figure **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-3 Chapter 6-Capture images PDA application and survey landing page in a 5 and 7 inch screens respectively

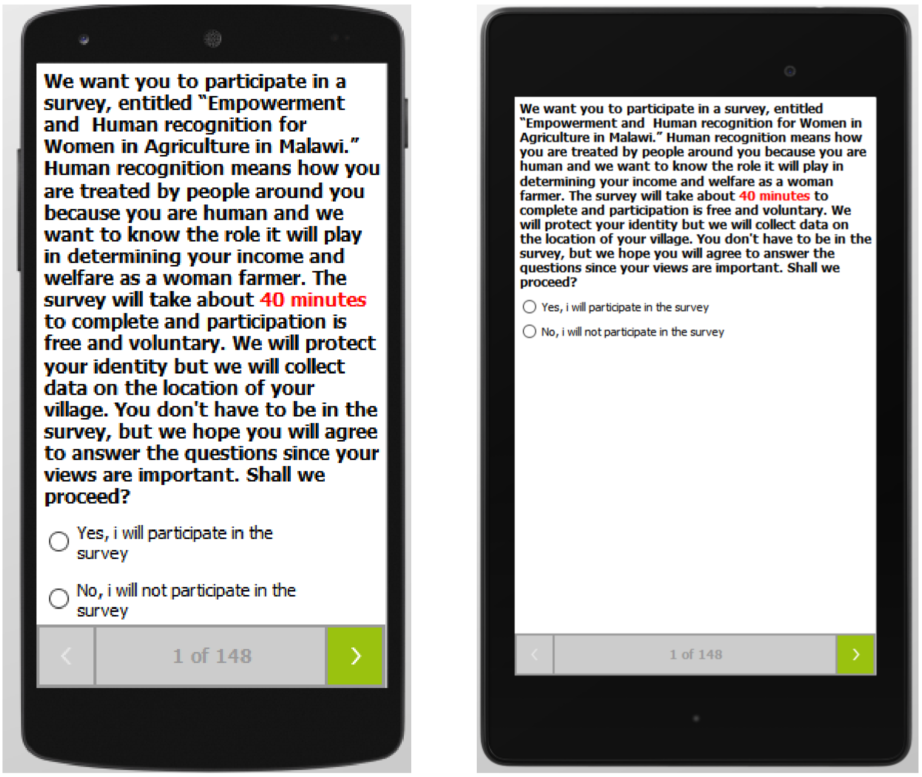


Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-2 Chapter 4-Summary of socio-demographic and socioeconomic factors

Factors	Explanatory Variables	Measurement	
		Malawi	Peru
Socio-demographic	Women status within the household	A dummy	A dummy
	Age of women and spouse/partner	Years	Years
	Religion	A dummy	-
	Ethnicity	A set of 9 dummies	A set of 3 dummies
	Marital union frequency	A dummy	A dummy
	Women's and spouse education	Single years	Single years
	Women's education squared	Squared single years	Squared Single years
Socioeconomic	Woman and spouse/partner occupation (agriculture)	Dummy	Dummy
	Wealth index	A set of 4 dummies	A set of 4 dummies
	Household owns agricultural land	A dummy	A dummy
	Women's work enumeration	A dummy	A dummy
Socioeconomic and demographic interactions	Household owns agricultural land and woman is an agricultural worker	Interaction	Interaction
	Household owns agricultural land and spouse is an agricultural worker	Interaction	Interaction
	Household owns agricultural land and woman's education	Interaction	Interaction
	Household owns agricultural land and spouse's education	Interaction	Interaction
	Woman is an agricultural worker and woman's education	Interaction	Interaction
Household characteristics	Sex of first child is female	A dummy	A dummy
	Sex of first two children are female	A dummy	A dummy
	Number of siblings born before the woman	Count	Count
	Household is polygamous	A dummy	-
	Household size	Count	Count
	Spouse/partner drinks alcohol	A dummy	A dummy
	Retaliation response	A dummy	A dummy
	Rural or urban	A dummy	A dummy
Country controls	Districts	A set of 24 dummies	A set of 23 dummies
Time controls	Year of survey	A set of 3 dummies	A set of 4 dummies
Time*occupation controls	Woman is an agricultural worker and year of survey	2 interaction variables	3 interaction variables

Notes: The placeholder "-"indicates that the indicator was not available in the dataset used in the analysis.

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-3 Chapter 4- Summary statistics of explanatory indicators for Malawi and Peru

	Malawi	Peru	Min	Max
Human recognition censored count	0.331***	0.191***	0	1
	(0.004)	(0.003)		
Agriculture: Partner	0.489***	0.339***	0	1
	(0.003)	(0.004)		
Agriculture: Woman	0.469***	0.362***	0	1
	(0.004)	(0.004)		
Head household: Woman	0.100***	0.077***	0	1
	(0.002)	(0.002)		
Spouse/partner age	34.1***	38.2***	15	80
	(0.084)	(0.060)		
Woman's Age	29.3***	34.4***	15	49
	(0.069)	(0.058)		
Wealth Index - poorest	0.170***	0.193***	0	1
	(0.003)	(0.003)		
- poorer	0.224***	0.264***	0	1
	(0.004)	(0.004)		
- middle	0.228***	0.249***	0	1
	(0.003)	(0.004)		
- richer	0.206***	0.171***	0	1
	(0.004)	(0.003)		
Spouse/partner Education	6.40***	9.08***	0	17
	(0.031)	(0.030)		
Women' Education	4.70***	8.44***	0	17
	(0.033)	(0.035)		
Household owns agricultural land	0.794***	0.407***	0	1
	(0.003)	(0.004)		
Household owns agricultural land…× Agriculture: Woman	0.412***	0.276***	0	1
	(0.003)	(0.004)		
× Agriculture: Partner	0.432***	0.243***	0	1
	(0.003)	(0.004)		
× woman's education	3.43***	2.54***	0	17
	(0.030)	(0.030)		
× partner's education	4.78***	3.07***	0	17
	(0.032)	(0.035)		
Agriculture: Woman × woman's education	1.87***	1.94***	0	17
	(0.022)	(0.029)		
Woman's education^2	35.3***	91.8***	0	289
	(0.389)	(0.630)		
Household size	4.86***	4.57***	1	10
	(0.016)	(0.013)		
Polygamy	0.142***		0	1
	(0.003)			
Woman is Muslim	0.140***		0	1
	(0.0026)			
Rural	0.865***	0.433***	0	1

	(0.003)	(0.004)		
No. older siblings	2.51***	2.90***	0	10
	(0.017)	(0.018)		
Married more than once	1.22***	1.09***	1	2
	(0.004)	(0.002)		
First child is female	0.463***	0.472***	0	1
	(0.003)	(0.004)		
First & second children: female	0.189***	0.176***	0	1
	(0.003)	(0.003)		
Alcoholic partner/spouse	0.339***	0.764***	0	1
	(0.003)	(0.003)		
Woman's physical retaliatory behavior	0.029***	0.081***	0	1
	(0.001)	(0.002)		
Work enumeration – Cash and kind	0.463***	0.082***	0	1
	(0.003)	(0.002)		
Observations	15,382	17,272		

Notes: Bootstrapped standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-4 Chapter 4-Percentage change in odds of human recognition deprivation in Malawi and Peru

Percentage change in odds (%)	Malawi			Peru		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Agriculture: Partner	8.6**	23.7**	14.9	-6.2**	-10.1	-8.2
Agriculture: Woman	8.0**	18.7	21.7*	5.4*	-31.5***	-34.8***
Head household: Woman	-27.2***	-30.5***	-27.6***	29.2***	15.9**	11.5
Spouse/partner's age	0.2	0.0	-0.0	0.1	0.7*	0.8**
Woman's age	-1.8***	-2.1***	-2.1***	1.1***	-0.5	-0.5
Wealth index-poorest	11.7	-9.6	-12.2	28.8***	66.6***	74.0***
-poorer	16.8**	-0.6	-1.5	70.0***	81.7***	73.4***
-middle	18.5***	4.5	1.5	81.6***	80.6***	71.1***
-richer	15.9**	5.7	3.7	55.2***	49.9***	45.4***
Spouse/partner's education	-1.0*	-3.2**	-2.8**	-0.7*	-3.2***	-4.1***
Woman’s education	0.1	4.3*	3.3	-3.8***	0.0	0.5
Household owns agricultural land	-	-17.7	-7.3		-25.2*	-30.8**
Household owns agricultural land….						
× Agriculture: Woman	-	-7.1	-8.1		-6.5	-1.1
× Agriculture: Man	-	-15.8	-16.5*		9.4	9.1
× woman’s education	-	1.0	1.0		-1.2	-1.7
× partner’s education	-	2.7	1.8		3.0**	3.3***
Agriculture: Woman …						
× woman’s education	-	-0.1	-0.8		1.3	1.3
Woman’s education^2	-	-0.5***	-0.5***		-0.2**	-0.3**
Household size	-	-1.1	-2.3**		4.5***	5.1***
Polygamy	-	27.4***	19.4***		-	-
Woman is Muslim	-	-37.4***	-20.3***		-	-
Rural	-	5.3	8.7		-8.6	-11.7**
No. of older siblings	-	1.3	1.2		0.6	0.9
Married more than once	-	22.5***	26***		187.0***	199.6***
First child is female	-	2.5	3.3		-8.0*	-8.2*
First & second children: female	-	-6.9	-7.9		12.1*	11.5*
Alcoholic spouse/partner	-	43.3***	40.4***		78.8***	71.9***
Woman’s physical retaliatory behavior	-	239.0***	248.5***		96.2***	90.9***
Work remuneration – cash and kind	-	28.7***	23.8***		-2.5	-1.2
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time×Occupation		Yes	Yes		Yes	Yes
Ethnicity controls			Yes			Yes
Country Fixed Effects			Yes			Yes
Observations	16,112	15,382	15,382	54,967	17,272	17,272

Notes: *Significance level: * at 10%, ** at 5%, *** at 1%; see table 1 for robust standard errors*

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-5 Chapter 4-Full model marginal effects on recognition deprivation censored count

	Malawi	**Peru**
	(3)	**(3)**
Agriculture: Partner	0.029	-0.012
Agriculture: Woman	0.040*	-0.061***
Head household: Woman	-0.067***	0.016
Partner/spouse age	-0.000	0.001**
Woman's age	-0.004***	-0.001
Wealth Index - poorest	-0.027	0.079***
- poorer	-0.003	0.079***
- middle	0.003	0.077***
- richer	0.008	0.054***
Partner/spouse education	-0.006**	-0.006***
Woman's education	0.007	0.001
Household owns agricultural land	-0.016	-0.053**
Household owns agricultural land × Agriculture: Woman	-0.017	-0.002
× Agriculture: Man	-0.037*	0.013
× woman's education	0.002	-0.003
× partner education	0.004	0.005**
Agriculture: Woman **x** woman's education	-0.002	0.002
Women's education^2	-0.001***	-0.000**
Household size	-0.005**	0.007***
Polygamy	0.037***	-
Woman is Muslim	-0.047***	-
Rural	0.017	-0.018**
No. of older siblings	0.003	0.001
Married more than once	0.048***	0.157***
First child is female	0.007	-0.012*
First & second children: female	-0.017	0.016*
Alcoholic partner/spouse	0.070***	0.078***
Woman's physical retaliatory behavior	0.257***	0.093***
Work remuneration – cash and kind	0.044***	-0.002
Observations	15,382	17,272

Notes: Robust standard errors calculated but not reported; *Significance level: * at 10%, ** at 5%, *** at 1%*

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-6 Chapter 5-Summary statistics of predictor variables used in the land access model

	Type	Mean		Min	Max
		All n= 5,499	Matrilineal, n = 2,435		
Land access (household agricultural landholding in ha)	Continuous	3.643 (3.760)	3.680 (3.818)	0	18
Negative human recognition	Continuous	3.135 (1.121)	3.160 (1.131)	0	8.41
Marital status: married (1 = yes, 0 = else)	Dummy	0.929 (0.258)	0.924 (0.265)	0	1
Household status: wife (1 = yes, 0 = else)	Dummy	0.854 (0.353)	0.868 (0.338)	0	1
Partner current age (years)	Continuous	34.882 (10.092)	34.512 (9.971)	15	70
Woman's current age (years)	Continuous	29.357 (8.338)	29.217 (8.269)	15	49
Woman's current age squared	Continuous	931.317 (533.375)	922.001 (529.135)	225	2401
Education: Woman (years)	Continuous	3.954 (3.231)	3.560 (3.165)	0	15
Education: Partner (years)	Continuous	5.679 (3.606)	5.225 (3.660)	0	17
Number of male household members older than 18 years	Count	0.957 (0.104)	0.899 (0.854)	0	6
Log of overall household size	Continuous	1.514 (0.396)	1.504 (0.395)	0	2.303
Partner(s) working as farmer(s): 1 = woman only, 2 = both partners	Count	1.66 (0.473)	1.690 (0.463)	1	2
Household:					
Owns a bicycle (1 = yes, 0 = else)	Dummy	0.525 (0.500)	0.542 (0.498)	0	1
Has electricity (1 = yes, 0 = else)	Dummy	0.018 (0.132)	0.016 (0.127)	0	1
Owns a radio (1 = yes, 0 = else)	Dummy	0.596 (0.491)	0.579 (0.494)	0	1
Owns a motorcycle (1 = yes, 0 = else)	Dummy	0.011 (0.104)	0.012 (0.108)	0	1
Has a landline telephone (1 = yes, 0 = else)	Dummy	0.010 (0.097)	0.090 (0.094)	0	1
Polygamy (1 = yes, 0 = else)	Dummy	0.145 (0.352)	0.154 (0.361)	0	1
Woman's remuneration as in-kind (1 = yes, 0 = else)	Dummy	0.039 (0.193)	0.048 (0.214)	0	1
Household wealth:					
Poorest (1 = yes, 0 = else)	Dummy	0.212 (0.409)	0.221 (0.415)	0	1

Poorer (1 = yes, 0 = else)	Dummy	0.269 (0.444)	0.294 (0.456)	0	1
Middle (1 = yes, 0 = else)	Dummy	0.262 (0.440)	0.249 (0.433)	0	1
Richer (1 = yes, 0 = else)	Dummy	0.197 (0.398)	0.186 (0.389)	0	1
Household owns livestock (1 = yes, 0 = else)	Dummy	0.644 (0.479)	0.600 (0.490)	0	1
Household is in a rural area (1 = yes, 0 = else)	Dummy	0.967 (0.178)	0.967 (0.178)	0	1
Woman's religion: Muslim (1 = yes, 0 = else)	Dummy	0.131 (0.337)	0.261 (0.439)	0	1
Woman owns the land that she farms (1 = yes, 0 = else)	Dummy	0.582 (0.493)	0.568 (0.496)	0	1

Note: Standard deviation in parenthesis.

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-7 Chapter 5-Summary statistics of predictor variables used in the nutrition model.

	Type	Mean			Min	Max
		Last child n = 4,750	2nd to last child n = 1,747	2nd to last & last child n = 1,579		
Mean agricultural household child dietary diversity per district	Continuous	2.675 (0.871)	2.684 (0.818)	2.684 (0.835)	1	6.55
Negative human recognition: 0-10, 0 = no negative recognition	Continuous	3.170 (1.119)	3.204 (1.127)	3.206 (1.122)	0	9.09
Marital status: married (1 = yes, 0 = else)	Dummy	0.926 (0.262)	0.932 (0.252)	0.928 (0.258)	0	1
Household status: wife (1 = yes, 0 = else)	Dummy	0.883 (0.322)	0.898 (0.303)	0.894 (0.308)	0	1
Partner current age (years)	Continuous	33.473 (8.611)	33.680 (7.791)	33.662 (7.795)	15	70
Woman’s current age (years)	Continuous	28.050 (6.971)	27.967 (5.965)	27.940 (5.901)	15	49
Woman’s current age squared	Continuous	835.395 (428.728)	817.702 (365.058)	815.474 (359.986)	256	240
Education: Woman (years)	Continuous	4.148 (3.263)	3.757 (3.182)	3.826 (3.196)	0	15
Education: Partner (years)	Continuous	5.796 (3.655)	5.473 (3.564)	5.557 (3.575)	0	15
Log household size	Continuous	1.585 (0.337)	1.695 (0.271)	1.699 (0.271)	0	2.303
Polygamy (1 = yes, 0 = else)	Dummy	0.134 (0.340)	0.129 (0.335)	0.131 (0.338)	0	1
Household wealth:						
Poorest (1 = yes, 0 = else)	Dummy	0.210 (0.407)	0.231 (0.421)	0.234 (0.423)	0	1
Poorer (1 = yes, 0 = else)	Dummy	0.267 (0.443)	0.265 (0.441)	0.265 (0.441)	0	1
Middle (1 = yes, 0 = else)	Dummy	0.258 (0.438)	0.274 (0.446)	0.271 (0.445)	0	1
Richer (1 = yes, 0 = else)	Dummy	0.198 (0.398)	0.178 (0.383)	0.175 (0.380)	0	1
Household: Owns agricultural land (1 = yes, 0 = else)	Dummy	0.874 (0.332)	0.879 (0.326)	0.880 (0.325)	0	1
Owns livestock (1 = yes, 0 = else)	Dummy	0.626 (0.484)	0.614 (0.487)	0.621 (0.485)	0	1
Partner is a farmer (1 = yes, 0 = else)	Dummy	0.652 (0.476)	0.661 (0.473)	0.659 (0.474)	0	1
First child is female	Dummy	0.495	0.492	0.493	0	1

(1 = yes, 0 = else)		(0.500)	(0.500)	(0.500)		
Second child is female (1 = yes, 0 = else)	Dummy	0.424 (0.494)	0.524 (0.500)	0.522 (0.500)	0	1
Age of last/smallest child (0-59 months)	Continuous	22.068 (14.784)		13.730 (9.082)	0	59
Last/smallest child: Height-to-Age Z scores	Continuous	-1.806 (1.507)		-1.787 (1.490)	-5.98	5.83
Age of Second to the latest child (0-59 months)	Continuous		44.433 (10.459)	44.610 (10.395)	0	59
Second to the latest child: Height-to-age Z scores	Continuous		-1.853 (1.604)	-1.836 (1.569)	-5.98	5.28
Region						
South (1 = yes, 0 = else)	Dummy	0.506 (0.500)	0.530 (0.499)	0.524 (0.500)		
North (1 = yes, 0 = else)	Dummy	0.134 (0.341)	0.120 (0.325)	0.120 (0.325)	0	1

Note: Standard deviation in parenthesis

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-8 Chapter 5- Estimates of land access for women in agriculture in Malawi

Land access (Household agricultural landholding in ha)	OLS	IV-2SLS	IV-LIML
Negative human recognition:	0.096**	0.977*	0.979*
0-10, 0 = no negative recognition	(0.039)	(0.568)	(0.568)
Marital status: married	-0.114	-0.120	-0.120
(1 = yes, 0 = else)	(0.171)	(0.179)	(0.167)
Household status: wife	-0.156	-0.475*	-0.476**
(1 = yes, 0 = else)	(0.129)	(0.251)	(0.241)
Partner current age (years)	0.007	0.003	0.003
	(0.009)	(0.010)	(0.010)
Woman's current age (years)	-0.068	-0.046	-0.046
	(0.041)	(0.045)	(0.045)
Woman's current age squared	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)
Education: woman (years)	0.004	0.007	0.007
	(0.016)	(0.017)	(0.016)
Education: partner (years)	0.028**	0.034**	0.034**
	(0.013)	(0.015)	(0.015)
Number of male household members	0.202**	0.158	0.158
older than 18	(0.092)	(0.101)	(0.097)
Log household size	0.721***	0.667***	0.667***
	(0.124)	(0.132)	(0.132)
Partner(s) working as farmer(s):	0.343***	0.327***	0.327***
1 = woman only, 2 = both partners	(0.091)	(0.095)	(0.095)
Household:			
Owns bicycle (1 = yes, 0 = else)	0.270***	0.263***	0.263***
	(0.091)	(0.096)	(0.096)
Has electricity (1 = yes, 0 = else)	0.096	0.273	0.273
	(0.395)	(0.413)	(0.358)
Has radio (1 = yes, 0 = else)	0.0024	0.034	0.034
	(0.103)	(0.109)	(0.107)
Owns motorcycle/scooter (1 = yes, 0 = else)	1.115**	0.953*	0.953**
	(0.507)	(0.547)	(0.434)
Has a landline telephone (1 = yes, 0 = else)	-0.104	-0.392	-0.393
	(0.533)	(0.577)	(0.489)
Polygamous (1 = yes, 0 = else)	0.295**	0.153	0.153
	(0.127)	(0.164)	(0.156)
Woman's remuneration: in kind	-0.725***	-0.985***	-0.986***
(1 = yes, 0 = else)	(0.204)	(0.276)	(0.277)
Household wealth:			
Poorest (1 = yes, 0 = else)	-1.116***	-1.081***	-1.081***
	(0.276)	(0.286)	(0.251)
Poorer (1 = yes, 0 = else)	-0.940***	-0.984***	-0.984***
	(0.256)	(0.263)	(0.228)
Middle (1 = yes, 0 = else)	-0.634**	-0.617**	-0.617***
	(0.252)	(0.259)	(0.219)

Richer (1 = yes, 0 = else)	-0.468*	-0.519**	-0.519**
	(0.246)	(0.253)	(0.217)
Household owns livestock	0.406***	0.378***	0.378***
(1 = yes, 0 = else)	(0.087)	(0.093)	(0.097)
Rural (1 = yes, 0 = else)	1.095***	1.078***	1.077***
	(0.192)	(0.207)	(0.248)
Woman's religion: Muslim	-0.228	-0.020	-0.020
(1 = yes, 0 = else)	(0.176)	(0.223)	(0.230)
Woman owns the land where she farms	0.178*	0.290**	0.290**
(1 = yes, 0 = else)	(0.105)	(0.134)	(0.140)
Constant	3.956***	1.319	1.311
	(0.720)	(1.893)	(1.853)
2 x Time controls	Yes	Yes	Yes
9 x Ethnicity controls	Yes	Yes	Yes
Observations	5,499	5,499	5,499
R^2	0.369	0.306	0.305
Adjusted R^2	0.365	0.301	0.300
Degrees of freedom	37	37	37
F-stat	88.27	78.74	78.34
First stage regression		IV-2SLS	IV-LIML
Difference from the median:			
- height		-0.001***	-0.001***
		(0.000)	(0.000)
- age at first sexual intercourse		0.014***	0.014***
		(0.005)	(0.005)
F-stat of excluded instruments		13.53	13.15
Overidentification: Hansen J-stat (p-value)		0.790	0.779
Endogeneity: Wu-Hausman test (p-value)		0.108	0.102

Note: Robust standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.-**9 Chapter 5-Estimates of land access for matrilineal women in agriculture in Malawi

Land access (Household agricultural landholding in ha)	Matrilineal (Yao & Chewa)		
	OLS	IV-2SLS	IV-LIML
Negative human recognition: 0-10, 0 = no negative recognition	0.167*** (0.0613)	1.210* (0.661)	1.539* (0.909)
Marital status: married	-0.343 (0.226)	-0.430* (0.248)	-0.457* (0.264)
Household status: wife (1 = yes, 0 = else)	-0.240 (0.199)	-0.642* (0.332)	-0.769* (0.417)
Partner current age (years)	0.009 (0.012)	0.0078 (0.013)	0.007 (0.014)
Woman's current age (years)	-0.061 (0.065)	-0.040 (0.069)	-0.033 (0.072)
Woman's current age squared	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Education: Woman (years)	-0.015 (0.022)	-0.016 (0.024)	-0.016 (0.025)
Education: Partner (years)	0.067*** (0.019)	0.065*** (0.020)	0.065*** (0.021)
Number of male household members older than 18	-0.439*** (0.087)	-0.474*** (0.091)	-0.475*** (0.091)
Log household size	0.269* (0.138)	0.216 (0.149)	0.199 (0.158)
Partner(s) working as farmer(s): 1 = woman only, 2 = both partners	0.431*** (0.135)	0.432*** (0.142)	0.433*** (0.149)
Household:			
Owns bicycle (1 = yes, 0 = else)	0.208 (0.134)	0.190 (0.144)	0.185 (0.152)
Has electricity (1 = yes, 0 = else)	0.609 (0.614)	0.917 (0.640)	1.015 (0.677)
Has radio (1 = yes, 0 = else)	0.0091 (0.155)	0.034 (0.165)	0.042 (0.172)
Owns motorcycle/scooter (1 = yes, 0 = else)	1.894*** (0.727)	1.823** (0.776)	1.801** (0.806)
Has landline telephone (1 = yes, 0 = else)	-0.591 (0.872)	-1.118 (0.867)	-1.285 (0.915)
Polygamous (1 = yes, 0 = else)	0.155 (0.189)	0.063 (0.209)	0.035 (0.225)
Woman's remuneration: in kind (1 = yes, 0 = else)	-0.445 (0.277)	-0.868** (0.413)	-1.002** (0.498)
Household wealth:			
Poorest (1 = yes, 0 = else)	-0.859** (0.401)	-0.786* (0.427)	-0.763* (0.447)
Poorer (1 = yes, 0 = else)	-0.609 (0.372)	-0.624 (0.393)	-0.629 (0.409)
Middle (1 = yes, 0 = else)	-0.363 (0.364)	-0.337 (0.384)	-0.329 (0.399)

Richer (1 = yes, 0 = else)	-0.157	-0.165	-0.168
	(0.354)	(0.373)	(0.387)
Household owns livestock	0.316**	0.301**	0.296**
(1 = yes, 0 = else)	(0.127)	(0.136)	(0.143)
Rural (1 = yes, 0 = else)	1.109***	0.812**	0.718*
	(0.256)	(0.329)	(0.381)
Woman's religion: Muslim	-0.188	0.0271	0.0950
(1 = yes, 0 = else)	(0.148)	(0.209)	(0.251)
Woman owns the land where she farms	0.276*	0.415**	0.459**
(1 = yes, 0 = else)	(0.153)	(0.190)	(0.215)
South (1 = yes, 0 = else)	-0.803***	-0.553***	-0.474*
	(0.141)	(0.214)	(0.264)
North (1 = yes, 0 = else)	-0.266	-0.265	-0.265
	(0.626)	(0.649)	(0.677)
Year 2010 (1 = yes, 0 = else)	-1.829***	-1.727***	-1.695***
	(0.272)	(0.294)	(0.311)
Year 2005 (1 = yes, 0 = else)	-5.115***	-5.543***	-5.678***
	(0.236)	(0.357)	(0.443)
Constant	4.096***	1.133	0.197
	(1.114)	(2.234)	(2.881)
Observations	2,453	2,453	2,453
R^2	0.410	0.324	0.261
Adjusted R^2	0.402	0.315	0.252
Degrees of freedom	30	30	30
F Stat	56.11	47.63	43.38
First stage regression		IV-2SLS	IV-LIML
First-born child is female		-0.075*	-0.075*
		(0.044)	(0.044)
Difference from the median:			
- height		-0.001***	-0.001***
		(0.000)	(0.000)
- age at first sexual intercourse		0.013*	0.013*
		(0.008)	(0.008)
F stat of excluded instruments		6.451	6.451
Overidentification: Hansen J-stat (p-value)		0.108	0.126
Endogeneity: Wu-Hausman test (p-value)		0.136	0.136

Note: Robust standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.**-10 Chapter 5-OLS estimates of district mean household child dietary diversity in households with women farmers only in Malawi

Household child dietary diversity (District Mean)	Last child	2nd to last child	2nd to last & last children
Negative human recognition:	-0.015*	-0.045***	-0.046***
0-10, 0 = no negative recognition	(0.009)	(0.014)	(0.015)
Marital status: married (1 = yes, 0 = else)	0.024	-0.026	-0.031
	(0.050)	(0.086)	(0.090)
Household status: wife (1 = yes, 0 = else)	-0.081**	-0.097	-0.102
	(0.038)	(0.068)	(0.072)
Partner current age (years)	-0.006**	-0.005	-0.007*
	(0.002)	(0.004)	(0.004)
Woman's current age (years)	0.009	-0.006	0.002
	(0.013)	(0.025)	(0.028)
Woman's current age squared	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)
Education: Woman (years)	0.002	0.004	0.004
	(0.004)	(0.007)	(0.007)
Education: Partner (years)	-0.005	-0.009	-0.010
	(0.004)	(0.006)	(0.006)
Log household size	-0.102**	-0.156	-0.200*
	(0.050)	(0.098)	(0.107)
Polygamy (1 = yes, 0 = else)	-0.072**	-0.015	-0.034
	(0.029)	(0.046)	(0.048)
Household wealth:			
Poorest (1 = yes, 0 = else)	-0.074	-0.159	-0.156
	(0.057)	(0.099)	(0.105)
Poorer (1 = yes, 0 = else)	-0.085	-0.126	-0.147
	(0.053)	(0.095)	(0.100)
Middle (1 = yes, 0 = else)	-0.093*	-0.167*	-0.195**
	(0.052)	(0.091)	(0.096)
Richer (1 = yes, 0 = else)	-0.087*	-0.140	-0.157
	(0.052)	(0.094)	(0.099)
Household owns agricultural land	0.088***	0.101**	0.109**
(1 = yes, 0 = else)	(0.032)	(0.047)	(0.051)
Household owns livestock	0.004	0.030	0.031
(1 = yes, 0 = else)	(0.025)	(0.036)	(0.039)
Partner is a farmer	-0.026	-0.022	-0.024
(1 = yes, 0 = else)	(0.025)	(0.039)	(0.042)
First child is female	0.022	0.012	0.014
(1 = yes, 0 = else)	(0.023)	(0.035)	(0.038)
Second child is female	-0.006	-0.011	-0.024
(1 = yes, 0 = else)	(0.023)	(0.035)	(0.038)
Age of last child	0.002*		0.003
(0-59 months)	(0.001)		(0.003)
Last child:	-0.008		-0.020*
Height-to-age Z scores	(0.007)		(0.011)

Age of Second to the last child (0-59 months)		0.000	-0.002
		(0.002)	(0.002)
Second to the last child: Height-to-age Z scores		-0.023**	-0.020*
		(0.011)	(0.012)
Region			
North (1 = yes, 0 = else)	0.553***	0.514***	0.500***
	(0.033)	(0.057)	(0.061)
South (1 = yes, 0 = else)	0.312***	0.272***	0.264***
	(0.033)	(0.053)	(0.055)
Year 2010 (1 = yes, 0 = else)	0.687***	0.686***	0.671***
	(0.038)	(0.063)	(0.065)
Year 2005 (1 = yes, 0 = else)	0.303***	0.346***	0.359***
	(0.027)	(0.045)	(0.047)
Constant	2.452***	2.953***	3.001***
	(0.212)	(0.426)	(0.466)
9 × ethnicity controls	Yes	Yes	Yes
Observations	4,750	1,747	1,579
R^2	0.224	0.241	0.240
Adjusted R^2	0.219	0.226	0.222
Degrees of freedom	34	34	36
F-Stat	58.13	22.75	19.00

Notes: Robust standard errors in parentheses; *Significance level: * at 10%, ** at 5%, *** at 1%*

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.-**11 Chapter 7-Endogenous observed and measurement variables and indicator questions

Latent grouping	Observed Variables	Indicator/questions
Latent variable: Self/household human recognition	Positive Human recognition	Generated using the Alkire foster method (see other table for indicators)
	Subjective human recognition	(Scale= 1 "Never True", 2" Not very true" 3 "Somewhat true" 4" Always true")
	Self-reported (SR) Subjective human recognition (self/household)	I am respected by my spouse and family My contributions are recognized by my spouse and family I am not treated inhumanely by my spouse and family
	Self-reported (SR) Subjective human recognition (community)	I am respected by non- family members in the community. My contributions are recognized by non- family members in the community. I am not treated inhumanely by non- family members in the community.
Latent variable: Land use behaviour	No of land use practices	Respondent used in the last cropping cycle, Improved seed variety Irrigation technology Crop rotation Herbicides or pesticides Other methods
	Decision-maker: Land improvements	The person that made the decision to improve the land is: (1) Inside/outside the household: someone else (2) Household jointly (3) Secondary respondent/spouse (4) Primary respondent
	Decision-maker: Input use	The person that made the decision which input to use is: (1) Inside/outside the household: someone else (2) Household jointly (3) Secondary respondent/spouse (4) Primary respondent
Latent variable: Self-reported community discourse participation	Public speaking	What is your level of comfort on public speaking to support community infrastructure: (1) No, not comfortable at all (2) Yes, but with great difficulty (3) Yes, but with little difficulty (4) Yes, fairly comfortable (5) Yes, very comfortable on public speaking to condemn misbehaviour of public officials: (1) No, not comfortable at all (2) Yes, but with great difficulty (3) Yes, but with little difficulty

		(4) Yes, fairly comfortable (5) Yes, very comfortable
Latent variable: Institutional recognition	Agent-reported: Ease of decision-making participation in the village	In your own opinion, Female village member can make binding decisions without their spouse or a male member of their family in village meeting in the following: (“yes” “No”) (1) Election of village officials (2) Village infrastructure (3) Use of Village resources (4) Other village activities
	Agent-reported: Ease of rights/property rights in the village	In your own opinion, victims of violence in your village can........ (“yes” “No”) (1) easily file for divorce (2) easily claim the general rights as a spouse or for their child(ren) in case of death of spouse (3) easily claim rights to joint property, alimony and child support (4) easily claim custody of child(ren) and visiting rights
		In your own opinion, (Scale= 1 “Never True”, 2” Not very true” 3 “Somewhat true” 4” Always true”)
	General community recognition	The community is able to meet the general need of its members The community is able to meet the financial needs of its members Members are treated equally in dispute resolution
	Female community recognition	Female members are treated equally in dispute resolution Female members have equal access to community resources Female members are always treated with respect Female members are always included in decision-making The community values and recognizes its female members contributions to decision making The community values and recognizes its female members as human beings.

Table **Error! Use the Home tab to apply Überschrift 8;Appendix to the text that you want to appear here.-**12 Chapter 7-Equation goodness of fit

Variance						
Dependent variables	Fitted	Predicted	Residual	R-squared	MC	MC2
Observed variables						
Deci: Land improv	0.808	0.062	0.746	0.077	0.277	0.077
Deci: Input use	0.774	0.049	0.725	0.063	0.251	0.063
No of land use practices	0.933	0.521	0.412	0.559	0.747	0.559
AR: G&F Comm.HR	1.444	0.829	0.615	0.574	0.758	0.574
AR: Ease decision	1.121	0.785	0.336	0.700	0.837	0.700
AR: Ease rights	0.389	0.334	0.055	0.859	0.927	0.859
SR: Subj. Self HR	3.943	2.008	1.935	0.509	0.714	0.509
SR: Subj. comm. HR	3.320	0.981	2.339	0.296	0.544	0.296
MDI: HR	2.279	1.044	1.234	0.458	0.677	0.458
PS: Infra	2.520	2.096	0.424	0.832	0.912	0.832
PS: Misbehaviour	2.358	1.770	0.588	0.750	0.866	0.750
Latent						
LUB	0.521	0.311	0.300	0.597	0.773	0.597
Par_comm	2.096	0.279	1.817	0.133	0.365	0.133
Overall				0.979		

Notes: MC = correlation between dependent variable and its prediction; MC2 = MC^2 is the Bentler-Raykov squared multiple correlation coefficient.

B. List of Publications

Paper 1: Maduekwe, E.; de Vries, W.T.; Buchenrieder, G. (2019). Measuring Human Recognition for Women in Malawi using the Alkire Foster Method of Multidimensional Poverty Counting. Social Indicators Research 95 (11), 1-20, https://doi.org/10.1007/s11205-019-02175-z

Authors' contribution: Maduekwe, E (55%).; de Vries, W.T. (20%); Buchenrieder, G. (25%)

Paper 2: Maduekwe, E.; de Vries, W.T.; Buchenrieder, G. (2019). Identifying Human Recognition Deprived Women: Evidence From Malawi and Peru. Journal of Development Studies 27, 1–21, https://doi.org/10.1080/00220388.2019.1666977

Authors' contribution: Maduekwe, E (55%).; de Vries, W.T. (20%); Buchenrieder, G. (25%)

Paper 3: Maduekwe, E.; Buchenrieder, G. (2019). The Effect of Human Recognition on Land Access and Child Nutrition: Evidence from Women Farmers in Malawi. (Working Paper).

Authors' contribution: Maduekwe, E (55%).; Buchenrieder, G. (45%)

Paper 4: Maduekwe, E.; de Vries, W.T. (2019). Random Spatial and Systematic Random Sampling Approach to Development Survey Data: Evidence from Field Application in Malawi. Sustainability, 11 (24), 6899, https://doi.org/10.3390/su11246899

Authors' contribution: Maduekwe, E (70%).; de Vries, W.T. (30%)

Paper 5: Maduekwe, E.; de Vries, W.T. (2020). Human Recognition and Land Use Behaviour: A Structural Equation Modelling Approach from Malawi. Book Chapter 6, Responsible and Smart Land Management Interventions: An African Context. Editors W.T. de Vries, John Bugri, Fathima Mandhu, CRC Press Taylor & Francis (Forthcoming).

Authors' contribution: Maduekwe, E (70%).; de Vries, W.T. (30%)

The authors whose names are listed immediately below indicate agreement that the above information is true and correct.

Author's name	Signature	Date
Maduekwe, E.		25.10.2019
Buchenrieder, G.	Gertrud Buchenrieder	28.10.2019
de Vries, W. T.		4.11.2019