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DOES RICE COMMERCIALISATION IMPACT ON LIVELIHOOD? EXPERIENCE FROM MNGETA IN KILOMBERO DISTRICT, TANZANIA

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ACRONYMS

AFRINT	Africa in Transition
APRA	Agricultural Policy Research in Africa
FGD	focus group discussion
FHH	female-headed household
HCI	Household Commercialisation Index
IDS	Institute of Development Studies
KOTAKO	Korea-Tanzania Company
KPL	Kilombero Plantation Limited
MHH	male-headed household
MPI	Multidimensional Poverty Index
MSF	medium-scale farmer
RCI	Rice Commercialisation Index
SAGCOT	Southern Agricultural Growth Corridor of Tanzania
SRI	System of Sustainable Rice Intensification
SSF	small-scale farmer

EXECUTIVE SUMMARY

This paper discusses the livelihood impacts of rice commercialisation for farmers in Mngeta division in Kilombero district in Tanzania. Rice commercialisation occurs where more farmers engage in factor markets and product markets, buying more inputs and selling more farm produce through the market, as opposed to subsistence production. In the study area, rice commercialisation has been an on-going process for a long time, but it seems to have been accelerating recently due to various factors. This paper outlines those factors in order to provide policy recommendations for enhancing the enabling factors for commercialisation, while addressing the inhibiting factors, particularly in relation to inclusive poverty reduction.

The analysis is based on a sample of farm households across ten villages that were randomly selected from all villages located 30km from Kilombero Plantation Limited (KPL), a large-scale rice farm in Mngeta division – which is the study area.[1] According to government policies and priorities, KPL was expected to have a positive commercialisation impact on surrounding farmers in terms of technology transfer and market access, especially for farm produce. The sample comprises 537 farm households (87.7 percent male-headed and 12.3 percent female-headed) who were interviewed in October 2017. Of these, 357 households (66.5 percent) were small-scale farmers (SSF) and 74 (13.8 percent) were medium-scale farmers (MSF), while 106 (19.7 percent) were members of farmer groups practicing System of Sustainable Rice Intensification (SRI) technologies. The sample was drawn from a population of 6,236 households comprised of 5,160 (82.7 percent) male-headed households (MHH) and 1,076 (17.3 percent) female-headed households (FHH). Out of the 6,236 households in the population 6,104 (97.9 percent) were SSFs and only 132 (2.1 percent) were MSFs.

Considering the strong influence of rural electrification on rice processing, as observed during preliminary visits to the study area, stratified sampling was employed, classifying villages in three categories according to their electricity status as follows: (i) had electricity by the 2016/17 production season; (ii) gained electricity between 2017/18 and 2018/19; and (iii) without electricity by 2019. This was done to allow assessment of spatial and temporal effects of electrification on rice commercialisation using panel data. The SSFs and MSFs were then sampled randomly from each selected village, with probability proportional to village size, using the list of households as the sampling frame. This was followed by post-stratification to obtain the sample of MSFs, since it was established that the definition of MSF varied between villages depending on land availability. A common definition was adopted during post-stratification, consistent with other studies on farm size in Tanzania.

This study examines the level of rice commercialisation in the study area and if such commercialisation is associated with a positive impact on farmers' livelihoods, as well as other people in the study area. Data were processed using a combination of descriptive and econometric methods; including a Tobit model to assess the influence of various factors on the Rice Commercialisation Index (RCI), and a logit model to assess the influence of RCI and other factors on the Multidimensional Poverty Index (MPI).

The findings show that rice commercialisation has been on-going in the study area. The mean RCI is 59.2 percent (median 65.2 percent), ranging from 50.8 percent for farmers cultivating less than 2ha to 79.7 percent for farmers cultivating more than 20ha. The RCI is significantly different across farmer categories and farm size ($p = 0.00$). However, comparison by sex of household head shows a lower level of significance ($p = 0.06$), while no significant difference exists between the mean RCI by village electricity status ($p = 0.5$).

The regression analysis for drivers of commercialisation reveals that the RCI is positively influenced by the household head's educational level, farm size, access to extension services, the ability to intensify rice production as well as the concentration of MSFs in a village. This final variable suggests that there are technological and knowledge spill-overs to SSFs from the presence of MSFs – a phenomenon that was also identified in initial qualitative work. By contrast, RCI is negatively influenced by household size and the distance of a farmer to the nearest large rice mill.

This latter variable reflects the impact of electrification on rice commercialisation, through improving market access.

In our RCI analysis, the coefficient for village electricity status is negative. However, this does not suggest that electrification discourages rice commercialisation – but that this relationship is likely to be mediated by other factors. In fact, the robust negative coefficient on the distance to the nearest large mill demonstrates that the opposite is true. Rather, we hypothesise that the negative coefficient on the electrification dummy variable is picking up the spill-overs from MSFs to SSFs, which are observed primarily in villages that are currently without electricity.

Rice commercialisation is promoted because of its expected positive influence on reducing poverty. In the current study, both the incidence and intensity of poverty are above 30 percent for all categories of farmers. The incidence is particularly high for FHHs, MSFs and famers in the lowest commercialisation quintile. The poverty-reducing effect of rice commercialisation is clearly reflected via a decreasing MPI score as RCI increases. This is consistent with field observations showing that farmers who live in remote villages tend to have less livelihood improving amenities (housing) and services (health, water, education), even though they score higher RCI levels.

The MPI will decrease if the following variables increase at the household level: education of household head, land size, membership of groups practising SRI; non-farm income, electrification and if a farmer moves to the upper two RCI quintiles. Meanwhile, declining livelihood changes are associated with increasing age of the household head, household size, if the household is headed by a female farmer, if a famer belongs to the MSF category as well as the second and third RCI quintiles. These will increase the MPI, hence, translating to higher poverty levels. This points to the need for targeted focus on the most vulnerable groups such as women and MSFs to address their constraints, even if they score higher RCI values and are commercialising more. Some of the initiatives to achieve this require more investment in public goods such as health and education infrastructure, but other interventions require more local mobilisation and awareness, including enforcing existing by-laws such as mandatory construction and use of toilets of acceptable standard, applying standing penalties for not sending children to school, and raising awareness to improve gender balance at household and community levels.

1 INTRODUCTION

1.1 The importance of rice in Tanzania

Rice is Tanzania's third most important staple after maize and cassava, produced by more than 1 million agricultural households, as well as many more actors and service providers along the value chain. Tanzania stands second after Madagascar for rice production in East, Central and South Africa; and is the leading producer and consumer in East Africa (URT 2016). In all producing areas, rice serves as a food and cash crop for farming households. About 70 percent of the rice produced by small-scale farmers (SSFs) is sold, hence the underlying importance of supporting inclusive commercialisation.

In Tanzania, rice production grew by 7.3 percent per annum from 2001–2011 (Stryker 2012 cited by Kilimo Trust 2014) and the trend is continuing, largely from area expansion (Kilimo Trust 2014), yet supply falls short of demand. Moreover, local supply is susceptible to annual weather variation since more than 90 percent of the production is rain-fed, by SSFs (URT 2016). Hence, deficits have been met through imports mainly from Asia, especially during the pre-harvest price spike. The demand gap presents a huge opportunity for actors in the rice value chain to increase production and hence commercialisation.

1.2 Why agricultural commercialisation?

Agricultural commercialisation has been defined as the process of agricultural transformation where farmers increasingly depend on markets to sell their products, but also for acquisition of inputs including labour (Poulton and Chinsinga 2018; Poulton 2017a). It is also interpreted as the aggregate response of many actors (farmers, input suppliers, transporters, millers) who choose different pathways in response to existing opportunities to increase the value of marketed farm produce. Agricultural commercialisation is generally a gradual incremental process driven by market demand, but it may be accelerated by external facilitation through public investment or action and by development agencies or social actors (Poulton 2017a; Wiggins *et al.* 2013).

Agricultural commercialisation is now widely sought by governments and development agents because it has been associated with agricultural intensification and productivity improvement (Djurfeldt *et al.* 2019), and/or farm expansion, both leading to rising marketed volume of farm produce. Rising income from such processes may contribute to livelihood improvement measured in terms of household assets, food security and hence, poverty reduction (Poulton 2017a). At the national level agricultural commercialisation is desirable for multiple reasons. Foremost, it contributes to food supply, keeping food prices down for growing urban demand. For tradable commodities such as rice, commercialisation generates foreign currency, and at advanced levels, a commercialised agricultural sector releases labour for employment in other sectors of the economy (Poulton and Chinsinga 2018).

The commercialisation process may however lead to undesirable outcomes, especially for SSFs, whose risk bearing threshold is very low. Price volatility in markets may expose them to more risk, and so do contractual arrangements that link SSFs with medium or large-scale farmers (Khamaldin, Wiggins and Mdoe 2013). In addition, household food security may be compromised where farmers expand their share of land for commercial crops or increase the share of staple crops sold. When commercialisation comes from area expansion by medium and large-scale farmers, SSFs may be squeezed out to near landlessness and destitution (Khamaldin *et al.* 2013). Moreover, a strong market demand pull for agricultural commodities may accelerate farm expansion into marginal and protected areas, with negative environmental impacts.

All these point to the fact that agricultural commercialisation will have different impacts on different people within an area, depending on how the factors impinge upon them, including their ability to respond to commercialisation opportunities around them. Such opportunities may include rising demand for agricultural commodities, rising demand for agricultural inputs and services, and reduced production costs from infrastructure improvement, as well as others.

1.3 Conceptual framework

This paper is guided by conceptual thinking from the Agricultural Policy Research in Africa project under the Future Agricultures Consortium, in six focal countries: Ethiopia, Ghana, Malawi, Nigeria, Tanzania and Zimbabwe. Commercial agriculture is expected to provide diverse opportunities for various people to engage in agricultural value chains, hence pursuing different pathways, depending on their opportunity space, a function of their resource endowment, and other factors. As stated earlier, however, not everybody gains from commercialisation processes. Some farmers may simply 'hang in' at the subsistence or semi-subsistence level if their options are limited by resource constraints or some other shocks in the family (Dorward 2009). Others may 'drop out' of agriculture when they fail to derive a sustainable livelihood from farming, often due to resource constraints (especially land and labour) and external shocks. This drives them into destitution, often as landless labourers. Guided by this broad framework, the study on rice commercialisation in Tanzania attempts to address the following questions. Do different commercialisation pathways lead to different livelihood outcomes? Who gains and who loses? What are the underlying reasons for such differences? How can rice commercialisation become more inclusive and have better outcomes in terms of livelihoods and food security, especially for women and girls? The findings from this study will inform policy debates and processes that strive to develop and implement agricultural development programmes consistent with the global Sustainable Development Goals with respect to poverty reduction, food security and equity.

The pace at which households respond to existing and emerging opportunities via commercialisation will differ depending on their resource endowment, risk aversion, location, as well as other personal and institutional characteristics. This will in turn have different impacts on people's livelihoods. In the past, several studies have examined the contribution of commercialisation to income poverty (Dube and Guveya 2016; Zhou, Minde and Mtingwe 2013). Whether such income is spent on livelihood improvement is, however, subject to a host of other factors, depending on who controls the household income and how it is spent (Ogutu and Qaim 2018). More robust indicators of poverty have since then been developed to capture a wider scope of factors that contribute towards improving the quality of life experienced by household members.

This paper endeavours to assess the level of rice commercialisation attained by different categories of farmers in the study area and determine whether the commercialisation process has been inclusive. The paper also identifies factors that influenced the level of rice commercialisation attained by households and factors that account for differences between farmers under the following categories (SSF, medium-scale farmer, membership of groups practicing System of Sustainable Rice Intensification, male-headed and female-headed households, and village electricity status). The paper also addresses the question of whether different categories of respondents, representing people in the study area (farmers, traders, business owners etc.) have benefited equally from rice commercialisation, measured by different indicators including: poverty incidence, intensity and the Multidimensional Poverty Index as well as food security.

2 METHODOLOGY

Data for this paper were collected as part of the Agricultural Policy Research in Africa (APRA) research programme that is being implemented in six African countries.[2] In Tanzania, the study on rice commercialisation is conducted in Mngeta division, Kilombero district within Morogoro region. The study area was selected because it fits well with the government ambition to link small-scale farmers (SSFs) with large-scale farmers under the Southern Agricultural Growth Corridor of Tanzania (SAGCOT)[3]. Kilombero Plantation Limited (KPL)[4] is a large-scale farm that covers about 5,800ha of land located in Mngeta division, surrounded by numerous SSFs and some medium-scale farmers (MSFs) in neighbouring villages. This farm was first established by the government of Tanzania during the 1980s under the management of Korea-Tanzania Company (KOTACO). After KOTACO pulled out, the farm went through several other management arrangements. Over time, a large part of the farm was left unattended, attracting squatters from surrounding villagers. In 2008, the government sold the farm to KPL, which revived rice production and introduced maize production as a second crop. This paper uses baseline data from APRA's (Tanzania) study on rice commercialisation under Work Stream One, a panel study, currently involving two cross sections or waves. Data for the first wave were collected in October 2017 from ten villages within a 30km radius of KPL. The second wave was scheduled for October 2019.

2.1 Sampling

2.1.1 Quantitative data

Preliminary visits to the study area established that commercialisation could not be attributed to one factor. Rather, interactions between several factors facilitated rice commercialisation in Kilombero valley. One of these factors was the role of rural electrification, which opened up a number of options for farmers and other residents. Other factors included: (i) land availability for farm expansion; (ii) migration of people and livestock, which has been associated with expansion of area under rice production; and (iii) the implementation of System of Sustainable Rice Intensification (SRI), a technology that has been promoted by KPL and other development agents, to improve rice productivity. Sampling was therefore designed to capture these underlying factors. The geographical area for the survey was restricted to 30km from KPL, thus covering villages in Mchombe, Mngeta and Chita wards within Mngeta division. The research design hinges on electricity status of villages, using the fact that rural electrification has been going on in the study area since 2015.

Stratification by electricity access allows comparison of immediate and longer-term effects of electrification from villages with and without electricity. Our working hypothesis is that higher rice prices and corresponding larger net returns will encourage farmers to respond by farm expansion and/or intensification. On-going studies on the emergence of medium-sized farms classify farms as medium-sized if they are between 5 and 20ha (Jayne *et al*. 2016). Three sub-populations of rice farmers were therefore initially defined as follows: SSFs if they cultivated 10ha or less; MSFs if they cultivated more than 10 ha; and SRI farmers. A few of these farms (16 percent) are actually larger than 20ha, the largest being 200ha. However, in relation to KPL such farms remain medium-sized.

The sampling frames for SSFs and the initial listing of MSFs were constructed with the assistance of key informants from each village selected in the initial stage of sampling. A list of SRI farmers was provided by KPL. The sample sizes from the three sub-populations were pre-set at 400 (SSF), 50 (MSF) and 100 farmers (SRI). After data collection, it became evident that the farm size criterion used to define SSF and MSF needed to be revised on account of variations across villages, which meant that both groups (SSF and MSF) had farmers with the same farm size. MSF farms were therefore post-stratified to avoid differences of classification across villages since the local definition varied depending on relative land abundance in the village.

A two-stage sampling design with stratification was used to select random samples of SSFs and MSFs. Electricity status of a village was used to define the strata as: (i) with electricity by 2016/17 (stratum 1 had

11 villages); (ii) villages that would have electricity by 2018/19 (stratum 2 had three villages); and (iii) villages that would not have electricity connected by 2019 (stratum 3 had eight villages), when the second stage of data should have been collected.[5] A total of ten villages were covered in the survey, of which four were selected from the first stratum, all three villages from the second stratum were sampled and three villages were selected from the third stratum. The representative villages from strata 1 and 3 were selected separately with probability proportional to size using the cumulative sampling method. However, one of the stratum 2 villages had to be moved to the first stratum after learning it had recently been connected, leaving two villages under the second stratum.

Simple random sampling was used to select 50 SSFs from each village and 100 SRI farmers from the list provided by KPL. The working sample of SSFs from each village was fixed at 40, and the extra ten were used as replacements in case of non-response or failure to locate a farmer. The number of MSFs from the villages sampled in the initial stage varied widely and it was decided to use proportionate allocation of the total sample of 50 MSF. The total sample from the three sub-populations had 559 households comprising of 408 SSFs, 50 MSFs and 101 members of SRI groups.

Data cleaning revealed that some respondents appeared in more than one group, or that they had provided incomplete responses. These had to be dropped from one list or reallocated to another. The final sample had 537 respondents comprising of 357 SSFs (66.5 percent), 74 MSFs (13.8 percent) and 106 SRI farmers (19.7 percent). The sample had 471 (87.7 percent) male-headed households (MHH) and 66 (12.3 percent) female-headed households (FHH). However, some of these respondents lacked key information for some of the question in the instrument. Hence the sample, which was used for computing the Rice Commercialisation Index (RCI)[6] and the Multidimensional Poverty Index (MPI), had 506 respondents (12.3 percent FHH and 87.7 percent MHH), comprising 330 SSFs (65.2 percent), 73 MSFs (14.4 percent) and 103 SRI farmers (20.4 percent). A detailed composition of the sample is presented in Annex 1 (a & b). Quantitative data were collected from these respondents by face-to-face interviews using a structured questionnaire, which had been pre-tested and corrected prior to the survey.[7]

2.1.2 Qualitative data

Qualitative data were collected during the same period from each of the ten villages, using focus group discussions (FGDs) and key informants; 116 farmers participated in FGDs (36.2 percent women, 63.8 percent men). There were 24 key informants (16.7 percent women and 83.3 percent men), including the farm manager of KPL, SRI coordinator from KPL and the District Agricultural Inputs and Cooperative Officer for Kilombero district. Qualitative data were collected to compliment information from the household survey, providing further insights on drivers of rice production and commercialisation from a temporal perspective, pathways and options for engaging in the sunflower value chain, and the corresponding impact on livelihoods, food security and inclusion.

2.2 Data analysis

We began by summarising qualitative data to identify key drivers of rice commercialisation in the study area since the 1980s, up to 2017. The key drivers included: establishment of a large-scale rice farm during the 1980s; improvement of transport and communication infrastructure; and the migration of agro-pastoralists into Kilombero valley, who brought with them aromatic and higher-yielding rice varieties, as well as animal traction. Rural electrification by the government further accelerated the improvement of communication infrastructure recently, especially since 2015.

2.2.1 Measuring commercialisation

Studies have shown that more commercialised households tend to have increased use of purchased inputs (Djurfeldt *et al*. 2019; Wiggins *et al*. 2013) and crop intensification, often measured by yields (Ochieng *et al*. 2016). The volume and value of crops sold have also been used to measure commercialisation (von Braun *et al.* 1994). Gabre-Madhin (2006) used four different measures of commercialisation including: (i) the ratio of value of sales of all crops produced by the household to the value of total production, often referred to as the Household Commercialisation Index (HCI); (ii) ratio of crop sales to total income; (ii) a household's net and absolute market position (net seller, net buyer or self-sufficient); and (iv) the income diversification or specialisation level. Each of these has its strengths and weaknesses. The HCI is most commonly used, having the advantage of being computed separately for each household. It has however been criticised for excluding livestock and livestock products, which may be more important than crops in some farming systems (Dube and Guveya 2016).

Computation of the HCI varies depending on a study's objectives and context. Many studies pioneered by Strasberg *et al*. (1999) have assessed a household's extent of commercialisation by computing the HCI as a ratio of gross value of all sales for all crops to the gross value of all crops produced. However, in this paper, considering its dominance, we only computed the commercialisation index for rice, hence referring to it as the RCI. We focus on rice because it is the most important cash crop in the study area, accounting for nearly 96 percent of mean household cash income from crops for the sample. Maize comes second at 1.9 percent while other crops including sweet potato, groundnut, beans, peas, cassava and banana each account for 0.1 percent or less. The RCI was computed as the percentage of rice (in paddy equivalent weights) that was marketed out of what was produced.

The data on rice production and sales were recorded at plot level. For sales, data were recorded on current sales and future sales. Unfortunately, total sales were under-estimated where no current sales were recorded from a given plot. In these cases, no data were solicited on future sales, to represent paddy that was held back by the farmer to sell later when the price rose. This posed a problem for the following reasons:

- Rice prices typically rise after Christmas, reflecting growing scarcity in the market, and one sign of a commercially orientated farm household is that it retains some rice for sale when prices rise.
- The influx of rice processing facilities, following electrification, has been accompanied by the establishment of rice warehousing, so as to encourage farmers to store their paddy at the mills ready for sale. As part of the competition between processors, farmers are allowed to store their paddy at the warehouse at minimal cost, on condition that they then process it for sale using the owner's rice mill (which is located on the same premises).
- Larger farmers have greater capacity to produce sufficient surplus, such that some paddy can be stored for several months until prices rise.

Therefore, there can be a systematic bias in the under-reporting of total sales, across small and medium-scale farms, arising from the under-recording of anticipated future sales. Hence, to deal with this limitation, for households where anticipated future sales were potentially under-recorded, we estimated total sales by a second method using the following accounting:

Total sales = Total production – (Total consumption + Quantity retained for seed + Gifts + Payment in kind).

The quantity of paddy retained for seed was estimated using the actual quantity of own seed used in the 2016/17 season. The quantity retained for household consumption was estimated using a prediction equation whose coefficients were estimated using Africa in Transition (AFRINT) project data[8] collected in 2017. The prediction equation was of the form expressed in Equation 1:

$$\widehat{q_i} = \widehat{\beta_0} + \widehat{\beta_1} AE_i$$

Equation 1

Where:

q_i = Predicted rice consumption by household 'i' in kg of paddy equivalent

AE_i = Household size in adult equivalents as defined by Claro *et al.* (2010)

First, AFRINT data were used to obtain coefficient estimates β_0 and β_1 by least squares method. Then, using APRA data, the size of each household in adult equivalents was determined, together with the estimated coefficients of 'q' were obtained. Second, the quantity given away and labour payments in kind were estimated by finding the average percentage of the production given away based on AFRINT data. The AFRINT average estimate was 6.72 percent (across the two categories). This percentage was applied to APRA total household production data to get the required estimate. Finally, the estimated total sales were only used for those households that satisfied both of the following criteria:

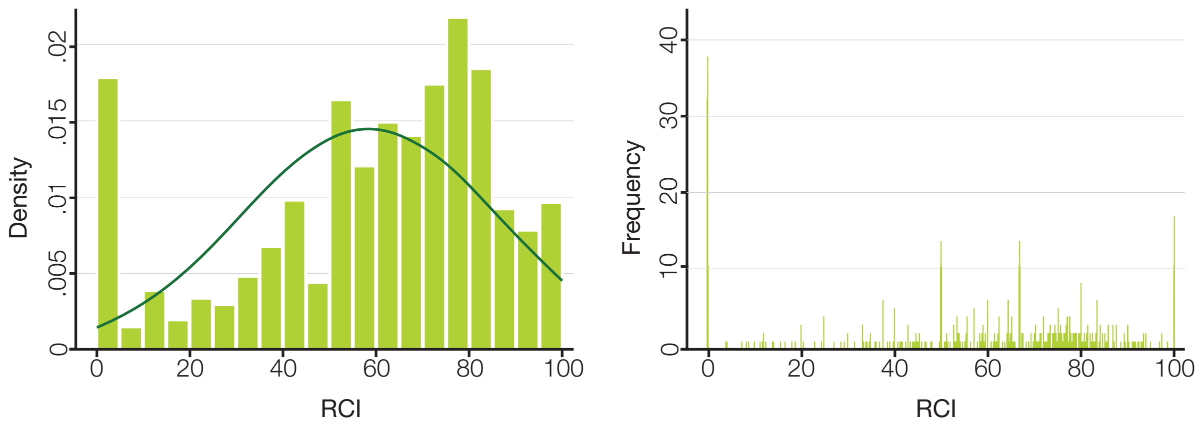
1. future sales were not registered for some plots, leading to potential under-reporting of total sales; and
2. estimated total sales exceeded the level of sales already recorded by the household.

The RCI varies from zero, where nothing was sold, to 100 percent where all produce was sold. Commercialisation levels were compared across SSFs, MSFs and SRI farmers. Comparisons were also made by sex of household head, as well as by village electricity status. The sample was divided into five RCI quintiles in order to assess whether the commercialisation process was inclusive, ranging from the lowest RCI (0–20 percent) up the highest (81–100 percent). The distribution of farmers across RCI quintiles is reported in Figure 3.1 and Annex 2.

2.2.2 Determinants of rice commercialisation

Looking at the histogram in Panel A (Figure 2.1) showing the distribution of RCI, we can see that there are quite

Figure 2.1: Examining the distribution of RCI



Panel A: RCI and density **Panel B: Frequency of RCI**

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

a few cases with RCIs equal to 0 and 100 – that one would expect looking at the rest of the distribution. Panel B further highlights the excess of cases where RCI is at 0 and 100.[9] Hence, a two limit Tobit model was used, reflecting corner solutions for RCI defined as a proportion, at 0 of RCI, which indicates no commercialisation, and at a value of 1 for RCI reflecting all rice is sold. A similar model has been used by Dube and Guveya (2016), Bekele and Alemu (2015), and Kirui and Njiraini (2013).

We estimate the following baseline equations:

$$RCI_i^* = \beta_1 \, Electricity_j \; + \beta_2 \, Intensification_i \, + \\ \beta_3 \, Electricity_j * Intensification_i \\ + \; \delta X_i + \; \varepsilon_i,$$

Equation 2

$$RCI_i^* \; = \gamma_1 \, MarketAccess_i \; + \gamma_2 \, Intensification_i \\ + \rho X_i + \; \varepsilon_i$$

Equation 3

The nature of the underlying latent variable implies that censoring occurs naturally over the unit interval. Hence, we estimate with two-sided censoring in both equations; using heteroscedasticity robust standard errors clustered at the village-level, where β_1 , β_2 and β_3 are the parameters of interests across the two models; δ and ρ are the vector parameters for the controls. ε_i is the error term.

Where 'j' is a notation representing a village and 'i' represents a household, our main variables of interest across the two models include: presence of electricity at village; *Marketaccess*$_i$ – market access variable (distance to the nearest large rice mill) household level; *Intensification*$_i$ farmer's response to commercialisation opportunities (extent of rice intensification), constructed as an additive score (0–4) using data on improved seeds, organic fertilisers, inorganic fertilisers, and pesticides, where each technology caries a score of one or zero for use or non-use by a farmer; and *Electricity * Intensification* – an interaction term that accounts for how intensification may mediate the relationship between RCI and electricity and vice versa (Equation 2).

X is a vector of control variables, namely: *household level attributes* (farm size, household size, level of education of household head, sex of household head, total household non-farm income, and access to extension services); and one proxy for *extensification* – number of MSFs in the village. The proportion of MSFs is higher in villages where land is still available for area expansion, including the creation of new farms (Isinika *et al.* 2018).

We expect farm size, level of education of household head, household total non-farm income and access to extension services to be positively correlated with RCI. It is debatable to what extent access to extension services is a household level attribute (reasonable if access is constrained by availability of extension staff in particular villages), as opposed to a farmer's response to commercialisation opportunities (if more enterprising farmers actively seek out extension staff for advice). We expect household size to be negatively correlated with RCI, as more rice is retained for home consumption. The sex of the household head = 1 when the household head is a woman, and we expect this to be negatively correlated with RCI as well. The total number of MSFs in a village could serve as an indicator of the potential for area expansion for rice cultivation since most of the agro-pastoralists use oxen for cultivation. However, as argued below, use of oxen may also be an indicator of the potential for technological and knowledge spill-overs from MSFs to surrounding SSFs through oxen rental services.

2.2.3 Measuring livelihood indicators

The immediate contribution of commercialisation at the household level is often measured in terms of income (Ogut and Quam 2018; Dube and Guveya 2016; Zhou *et al.* 2013) or the value of sales (Cazzuffi, Mackay and Perge 2018). However, using income as a proxy for livelihood status has been criticised (Ogutu and Quam, 2018; Kirui and Njiraini 2013) since it has been argued that household income only reflects potential wellbeing. Depending on intra-household relations and who controls the income, it may not be spent to improve nutrition and/or increase household assets that improve the quality of life in terms of education, health, and household assets. Moreover, depending both on individual attributes and the availability of services in a locality, the cost of translating income into wellbeing can vary considerably across households (Sen 1999).

Poverty may also be measured using different indicators including consumption-based indictors (such as the sum of household consumption expenditure), income-based indictors such as total net income, and subjective indicators based on self-assessment such as the subjective ladder. Others are asset-based indicators, which include the type of housing, asset indices and inequality-based indicators such as the Lorenz curve and the Gini coefficient (Chirwa *et al.* 2017). The MPI as proposed by Alkire and Santos (2014) and Alkire *et al.* (2016) seems to provide a better alternative since it captures a wider range of variables including assets, health, education and nutrition that reflect the quality of life within a household.

The MPI uses a set of vulnerability indicators to determine the incidence of poverty (headcount) and the intensity of poverty (degree of deprivation). At the population level these two indicators are combined to compute the MPI. A poverty cut-off point of 33.3 percent identified people whose deprivation score exceeds this threshold as 'multidimensional poor' (Akire *et al*. 2016). Hence, the overall MPI represents a proportion of the sample which is poor. Being representative of the population from which the sample is drawn, higher scores represent more deprivation, hence deeper poverty. The entire list of indicators that are used to compute the MPI is summarised in Annex 6.

Further, the MPI deprivation score is compared with the respondents' self-assessment of poverty which was obtained using the subjective ladder. Such comparison is considered useful because it is assumed that a person's perception of their poverty status will influence their effort to get out of it, since addressing poverty requires action (Hajek 2013). But self-assessment may also lead to inaction if it is perceived that there are no possibilities of escaping poverty.

2.2.4 Determinants of poverty status

To establish factors that account for a household's poverty status, the analysis uses a logit model to identify factors determining the likelihood of a household to be poor based on a number of poverty indicators. In this study we consider the following: (i) poverty incidence (headcount); (ii) intensity of poverty; (iii) MPI deprivation score; and (iv) subjective poverty. Descriptive analysis and the logit model are proposed for this type of analysis because it avoids the problem of endogeneity, since a farmer's poverty status most likely influences their RCI level and vice versa, which means, ordinary least squares would provide biased coefficient estimates (Ogutu and Quaim 2018; Alkire *et al.* 2016).

To study the relationship between MPI and commercialisation, we estimate the following baseline equation:

$$MPI_i^* = \beta_1\, Electrification_j \; + \gamma RCI_{iq} \\ + \delta X_i + \; \varepsilon_i$$

Equation 4

Where:

MPI_i^* represents a dummy variable, taking a value of one if a household is MPI poor, and zero otherwise RCI_{iq} represents a dummy variable, taking a value of one if a household is MPI poor, and zero otherwise represents a dummy variable that identifies the RCI group using *q* quintile for the household *i*. γ is the vector of parameters across the quintiles. All other variables are as previously defined.

MPI status of a household is defined as a dichotomous variable; a household being "MPI poor" if its score was above the 0.33 (or 33 percent) cut-off point, and not MPI poor otherwise. Using the logit model where a household's MPI score is the dependent variable, the analysis addresses the question, what is the probability of a household being multidimensionally poor? As defined earlier, a cut-off point of 33 percent distinguishes households that are MPI poor from others which are not. The relationship between the MPI and explanatory variables is briefly described in Annex 5. The estimated change (increase/decrease) in the probability (likelihood) of a household being classified as poor when a quantitative variable increases by one unit is the increase/decrease in the mean probability of being classified as poor when comparing two classes of a qualitative variable such as one level of RCI compared to farmers who are less commercialised. Explanatory variables for determinants of a household's multidimensional poverty status are presented in Annex 7.

3 RESULTS

Preliminary assessment[10] of the interaction between small-scale farmers (SSFs) and KPL show that employment effects were weak (both casual and permanent). However, the effect of technology transfer via training on System of Sustainable Rice Intensification (SRI) technologies and related credit facilitation had positive effects and the adoption rate, though low initially, is expected to increase as long as early adopters continue to outperform farmers who use traditional agronomic practices. The performance of SRI farmers therefore reflects the technology spill-over from KPL. Attempts to establish market linkages were weak and they were not sustained.

3.1 Distribution of RCI by categories

The Rice Commercialisation Index (RCI) was computed as the proportion (percent) of rice sold out of what was produced. All harvest and all sales – originally reported in terms bags of paddy or rice of different sizes – were converted to kilograms of paddy equivalent. Results of RCI by different categories of farmers are summarised in Table 3.1. The mean RCI for the whole sample was 59.2 percent – highest for SRI farmers (66.6 percent), followed by medium-scale farmers (MSF) (65.4 percent), and lowest for SSFs (55.5 percent), with a p-value equal to zero (p = 0.00). All median values were higher than the mean implying that more than half of the sample in each stratum scored an RCI value above the mean. The RCI scores for male-headed households (MHHs) were higher (60 percent) than those of female-headed households (FHH) (53.1 percent), and the difference was significant (p = 0.06). This can be explained by the lower mean land holdings by FHHs (1.8ha) compared to MHHs (3.7ha), and corresponding lower volume of rice harvested (2,999.7kg for FHHs compared to 6,386.7kg for MHH), hence a lower proportion of sales from FHHs. Farmers in villages with electricity essentially scored the same RCI mean value (60.2 percent) as those in villages without electricity (58.4 percent) because, as explained earlier, the effect of electricity on rice commercialisation while indirect, manifested through other variables such as distance from electric-powered milling centres and the price of milled rice. The higher proportion of SSFs (70.5 percent) in villages without electricity also reduces the mean RCI for this category, even though MSFs score a higher RCI value.

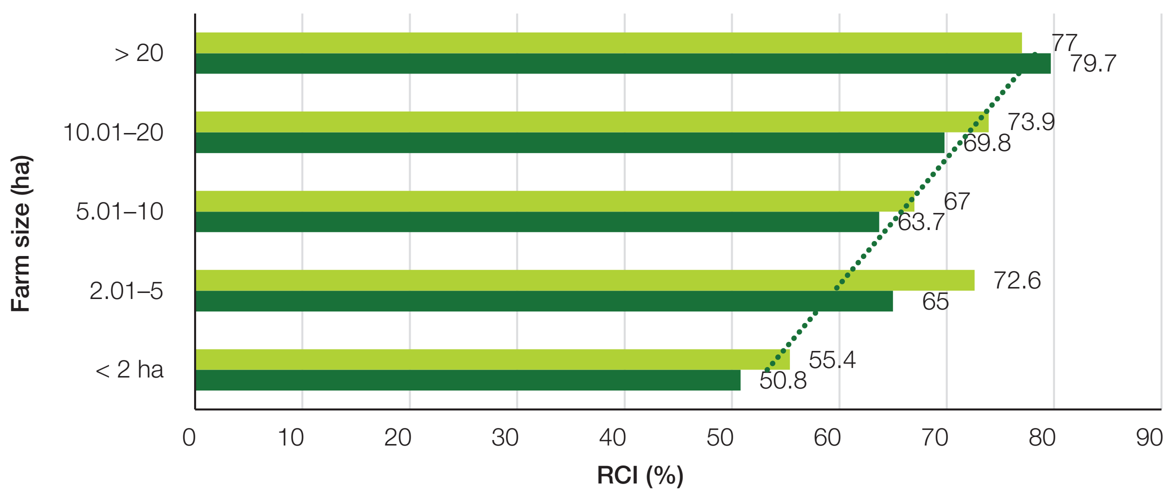
In the study area, rice is the most important crop, planted on 74.6 percent of the farm plots, compared to only 18.8 percent for maize and, within plots, rice covered 97 percent of the land (Isinika *et al.* 2018).

Table 3.1 RCI by farm household characteristics (%)

Category	Farmer characteristic	Mean RCI	Median RCI	Significance of difference (for RCI mean)
Farmer category	SSF	55.5	60.0	F = 8.78
	MSF	65.3	70.8	p = 0.00
	SRI	66.6	74.1	
Head of household	Female	53.1	59.0	F = 3.462
	Male	60.0	66.7	p = 0.06
Electricity status	With electricity	60.2	67.0	F = 0.55
	Without electricity	58.5	64.3	p = 0.5
Farm size	< 2ha	50.8	55.4	F = 10.9
	2.01–5ha	65.0	72.6	p = 0.00
	5.01–10ha	63.7	67.0	
	10.01–20ha	69.8	73.9	
	> 20ha	79.7	77.0	
Sample mean		59.2	65.2	

Source: Authors own, based on analysis using round one data from APRA Tanzania survey (2017)

Figure 3.1 RCIs by farm size



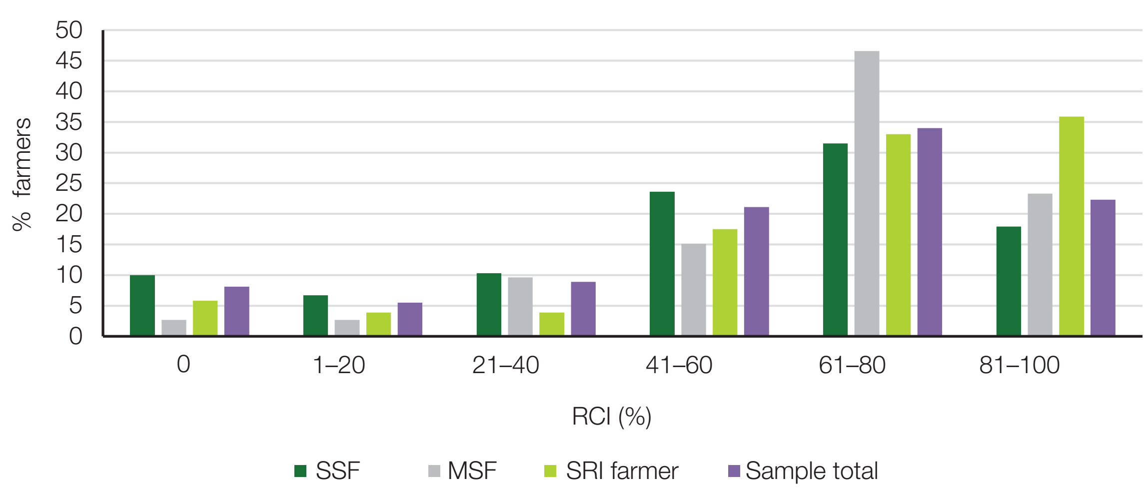
Source: Authors own, based on analysis using round one data from APRA Tanzania survey (2017)

Hence, farm size is highly correlated to the total area under rice. The results show that there is an increasing trend of RCI values as farm size increases, ranging from 50.8 to 79.7 percent (Table 3.1). However, the mean values mask significant variations that may exist within farmer categories.

Figure 3.1 presents the RCIs computed for the entire sample by farm size, from the lowest (0–20 percent) to the highest (81–100 percent) while Figure 3.2 represent the same farmers by category. We find a general upward trend of both the mean RCI and median values, the highest (79.7 percent) being for households with farms larger than 20ha, implying that farm expansion is associated with greater levels of rice commercialisation. We also note that the farm size 2.01–5ha performs better than the larger farm category of 5.01–10ha, probably due to more efficient use of purchased productivity enhancing factors including purchased seed, inorganic fertiliser and adoption of SRI technologies. This finding supports the inverse relationship between farm size and productivity, such that productivity declines with an increase in farm size (Apata, Sanusi and Olajorin 2016; Mahmood *et al.* 2014; Mugera and Langemeier 2011; Helfand and Levine, 2004). The analysis shows that about 53.1 percent of SRI farmers who scored the highest RCI fall under this category.

Despite these variations, the mean RCI values are not very different by sex and electricity status (Table 3.1). The median RCI was highest for SRI farmers

Figure 3.2 Proportion of farm households by RCI and farmer category



Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

Table 3.2 Proportion of production that was being held for future sales

Category	Mean (%)	Median	Significance
SSF	37.4	34.6	F = 8.9 p = 0.00
MSF	53.2	50.7	
SRI	50.7	57.2	
With electricity	49.5	51.0	F = 11.2 p = 0.001
Without electricity	38.1	37.8	
Female	43.0	42.9	F = 0.076 p = 0.782
Male	41.5	41.2	
Sample	**42.8**	**42.7**	

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

(71.1 percent) while for farm size the largest farmers (> 20ha) recorded the highest median RCI (77 percent). According to these findings, households that did not sell rice (RCI = 0 percent) and hence were not commercialised at all, represented 8.1 percent of the sample, the proportion being highest among SSFs (10 percent) and lowest among MSFs (2.7 percent). This explains the high proportion of SSFs in the lowest quintile (Figure 3.2).

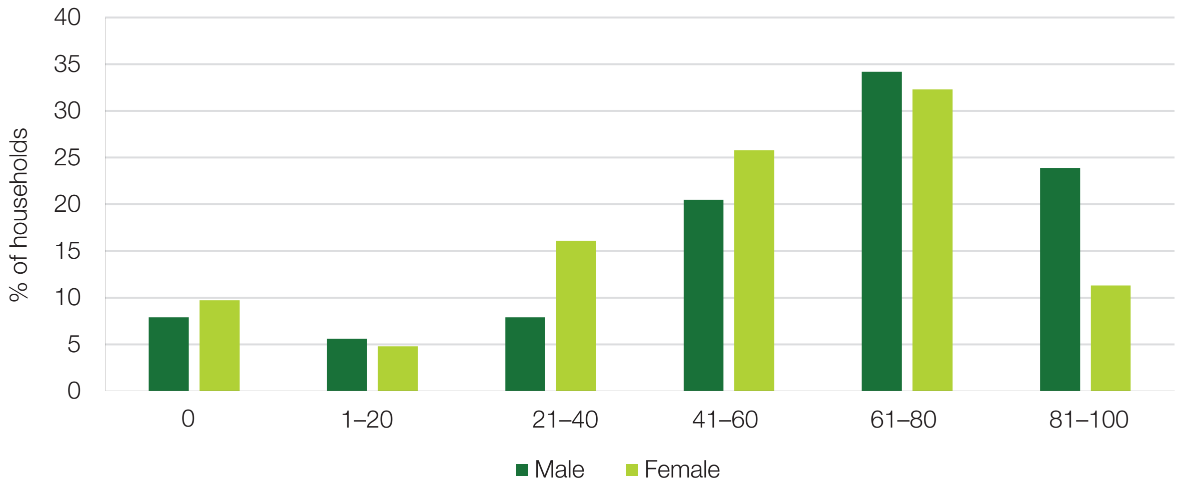
More than 50 percent of SSFs scored an RCI of 60 percent or less, while close to 70 percent of MSFs and SRI farmers scored RCI values above 60 percent. There were 25 farmers who were fully commercialised, selling 100 percent of what they produced. They represented 4.9 percent of the sample, being highest among SRI farmers (9.8 percent), followed by SSFs (4.2 percent) and MSFs (1.5 percent). Only one (4 percent) out of the 25 households was female-headed. Surprisingly, most (56 percent) of the fully commercialised farmers were SSFs. Only one (4 percent) was a MSF while ten (40 percent) were SRI farmers. Some of the farmers who sell all the paddy they produce could be taking credit from local money lenders or warehouses owners. At harvest time they are obliged to repay the loans in terms of paddy. The current (January 2020) credit rate stands at TSh 40,000 (US$17.32) in return for 100kg of paddy.

Focus group discussions (FGDs) reported that some of the large farmers in the study area send their paddy for storage in Ifakara town (the district headquarters) before the roads become impassable around February. They do this in order to sell at a higher price later in the year (Isinika and Mwajombe 2018). The proportion of reported future sales[11] (Table 3.2) confirms this assertion since MSFs (53.2 percent) and SRI farmers (50.7 percent) stored a significantly higher proportion of rice for future sales, compared to 37.4 percent among SSFs. Nevertheless, this still means that SSFs store more than one third of their harvest for future sales. It was reported during FGDs, and observed during visits to rice mills, that many farmers store their paddy at rice mills to wait for higher prices (Isinika and Mwajombe 2018). The proportion of future sales was significantly higher in villages with electricity (49.5 percent; F-value = 11.2) compared to those without electricity (38.1 percent). Surprisingly, FHHs stored fractionally more of their paddy than MHHs, but the difference was small (F-value = 0.076).

Figure 3.3 disaggregates RCI scores by quintile and gender. Columns for MHHs and FHHs each sum to 100 percent across the quintiles, but MHH are more numerous in absolute terms. A higher proportion of FHHs than MHHs is found in the lower quintile (1–3). In contrast, within the upper two quintiles (4 and 5), the proportion of MHHs is higher, by a factor of two at the highest quintile (Figure 3.2), implying that a higher proportion of MHHs sell a larger share of what they produce. This, as explained earlier, is due to the fact that MHHs cultivate a larger mean area and harvest more paddy on average, hence have a larger share of sales. Djurfeldt (2018) similarly shows that FHHs sell less proportionally because they produce less in absolute terms. The fact that MHHs score a higher RCI (60 percent) compared to FHHs (53.1 percent), as reported in Table 3.1, points to the need for deliberate efforts to increase production, first through intensification on current land holdings which may in due course enable them to acquire or rent more land, hence improve their RCI scores.

We have found that the distribution of farm households by quintiles, based on whether they come from villages with or without electricity (Figure 3.4), follows a similar pattern to that relating to RCI and sex of the household head (Figure 3.3), and that between RCI and farmer category (Figure 3.2). For households that did not sell rice (RCI = 0 percent), the proportion is higher in

Figure 3.3 Proportion of farm households by RCI quintile and gender of household head

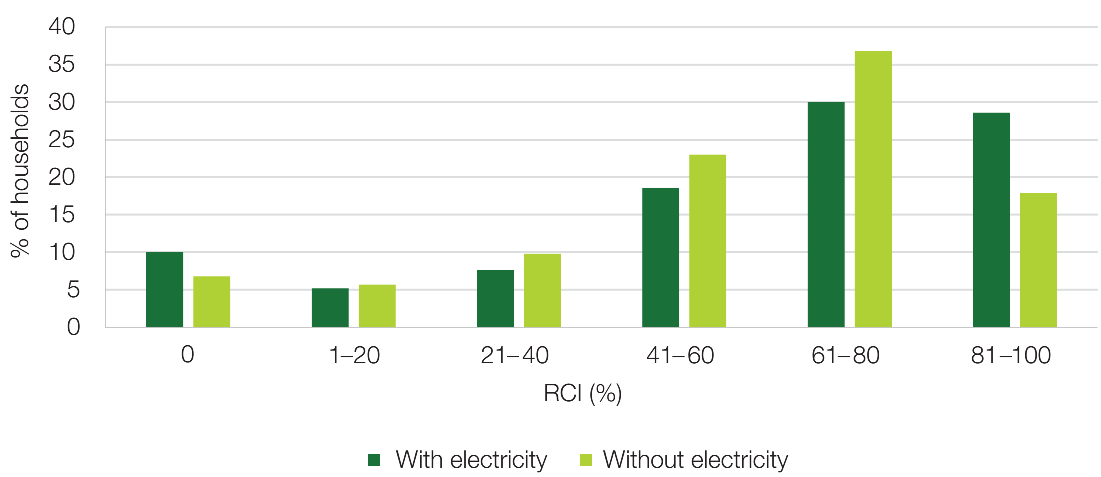


Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

villages with electricity, and is dominated by SSFs, which raises their proportion in the first quintile. Also, the same villages have a higher proportion of farmers in the highest quintile (RCI 81–100 percent), which may be explained by the fact that the majority (70.9 percent) of the SRI farmers, who scored the highest mean RCI (66.6 percent), reside in electrified villages, compared to only 19.2 percent and 37.3 percent of MSFs and SSFs respectively. However, the proportion of farmers is higher in villages without electricity for the third and fourth quintiles (Figure 3.3).

Table 3.3 shows the distribution of farm household types across villages with and without electrification, and also the mean RCI score for each household type by village electrification status. As hypothesised, MSF and SRI households each achieve a higher mean RCI value in villages with electricity, where access to output markets through modern processing facilities is easier. Surprisingly, however, the opposite is true for SSFs, who are found predominantly in villages without electricity within our sample. We return to this point later to explain how farmers respond to improved milling options following electrification within their own, or in neighbouring, villages. Our hypothesis is that there are technological and knowledge spill-overs from MSFs to SSFs and that these occur primarily in villages without electricity, where the majority of MSFs (81 percent in our sample) have settled. As the most recent immigrants into villages, most MSFs have acquired land in villages that were less densely populated, further from main roads and where electricity has not yet been connected. Farmers in villages with electricity tend to be along the main road, and face more land

Figure 3.4 Proportion of farm households by RCI quintile by village electricity status



Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

Table 3.3 Distribution of farm households by village electricity status and RCI score

Farmer category	With electricity		Without electricity		Mean RCI Whole sample
	(% households)	Mean RCI	(% households)	Mean RCI	
SSF	37.3	53.2	62.7	56.9	55.5
MSF	19.2	70.6	80.8	64.1	65.4
SRI	70.9	70.0	29.1	58.6	66.6
Sample	41.5	60.2	58.5	58.5	59.2

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

constraints, hence they have smaller farms, with less potential for farm expansion.

3.2 Distribution of RCI by other influencing factors

In addition to farmer category, farm size, gender and electricity status, the analysis in Annex 3 also assesses how the farmers' response to commercialisation opportunities influenced the distribution of farmers across RCI quintiles. The findings show that use of inorganic fertiliser, organic manure, tillage services, extension services, mobile money services, and livestock ownership contributed to significant differences in the level of commercialisation. Agricultural intensification is a common response to commercialisation opportunities (Ochieng *et al*. 2016), often measured in terms of yield. The mean rice yield presented in Table 3.4 is 2,4991.7kg/ha for the whole sample, being significantly higher for SRI farmers (2,841.5kg/ha) followed by SSFs (2,476.5kg/ha) and lowest for MSFs (2,071.1kg/ha) implying lower intensification levels. However, MSFs recorded the highest volume of rice sale per household (16,761.7kg), which is more than twice, and almost five times, the volume harvested by SRI farmers and SFFs respectively.

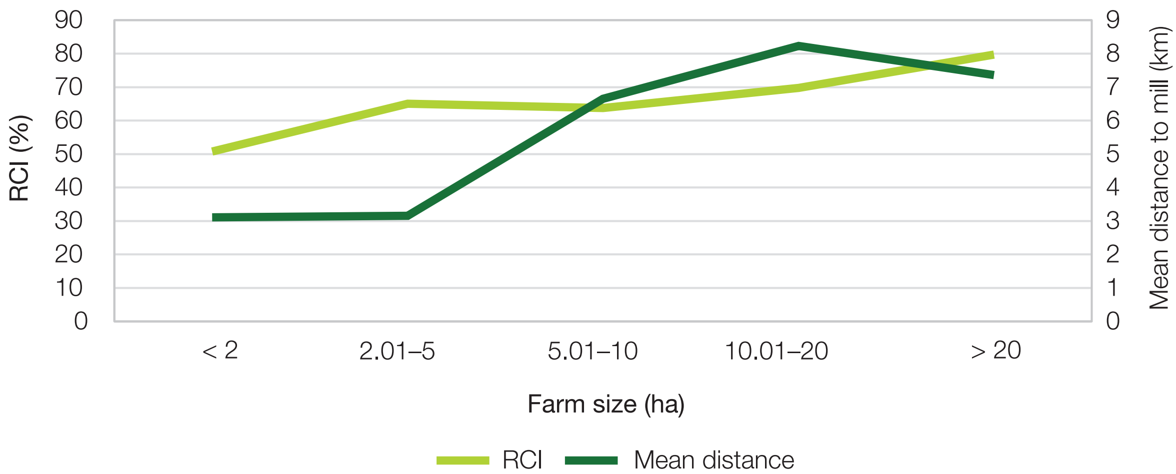
FHHs obtained lower yields at 2,424kg/ha compared to 2,501.1kg/ha for MHHs but the difference was not significant (F = 1.82). FHHs also produced a lower mean volume of rice (2,999.7kg), which was nearly half (47 percent) of the mean volume produced by MHHs (6,386.7kg) and a lower corresponding median value. Hence, the RCI for FHHs is lower (Table 3.1). The

Table 3.4 Mean and median yield levels

Category	Farmer characteristic	Yield		Significance of difference
		Mean	Median	
Farmer category	SSF	2,476.5	2,409	F = 6.96***
	MSF	2,071.1	1,853	
	SRI	2,841.5	2,630	
Sex	Female	2,424.0	2,372	F = 0.17
	Male	2,501.1	2,426	
Electricity	With electricity	2,675.2	2,595	F = 6.51***
	Without electricity	2,360.4	2,224	
Farm size (ha)	< 2ha	2,468.0	2,524	F = 1.82
	2.01–5ha	2,645.5	2,471	
	5.01–10ha	2,338.6	2,193	
	10.01–20ha	2,000.9	1,622	
	> 20ha	2,146.5	2,446	
RCI quintile (%)	1–20	1,543.6	1,212	F = 15.52***
	21–40	2,174.2	1,100	
	41–60	2,462.6	2,471	
	61–80	2,547.6	2,446	
	81–100	3,097.8	2,842	
	Sample mean	**2,491.7**	**2,409**	

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

Figure 3.5 RCI and mean distance to nearest mill by farm size



Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

proportion of FHHs is higher at lower commercialisation levels (quintiles 1–3) as reported in Figure 3.2. Since rice sales from FHHs come from a lower production level due to smaller farms and lower yield, they may represent distress sales (Isinika *et al.* 2018).

Farmers in villages with electricity obtained significantly higher yields of 2,675.2kg/ha compared to 2,360.4kg/ha for farmers in villages without electricity (F-value = 6.51). Since they face more land constraints, they are more inclined to respond to commercialisation opportunities by using productivity enhancing inputs (improved seed, inorganic fertiliser, herbicides, farm yard manure), but the adoption rate for such technologies tends to be slower than farm expansion where farmers in villages without electricity respond almost immediately by expanding their farms, leading to a larger marketed surplus. Farmers who owned holdings larger than 20ha had the highest mean RCI scores (79.7 percent) and all of the farmers in this category sold at least 40 percent of their harvest (Annex 3). This is consistent with on-going studies on the emergence of medium-scale farms (Jayne *et al.* 2016), which argue that most of the MSFs who take up farming, expand and intensify production, seeking profit as commercial farmers. Close to one third (32.1 percent) of the farmers with the smallest holdings (< 2ha) fell in the lower three quintiles (RCI ≤ 40), representing low to moderate commercialisation levels.

At first glance, Figure 3.5 suggests a positive relationship between RCI and distance to the nearest large processing mill. However, this is misleading. The mean distance to the nearest large mill is 0.9km and 6km for villages with and without electricity respectively.[12] Figure 3.4 reflects the fact that farmers who own larger farms – and who have generally acquired them fairly recently – tend to be located in more remote villages where land is available for farm expansion. As will be shown below, in multivariate analysis, distance to the nearest large processing mill shows a robust negative relationship with RCI.

In some villages without electricity, road access can be challenging, especially during the rains when some households can only be reached by boat. This, combined with the aggregation function provided by rice processors, reduces trader competition for rice purchased from farmers in such villages. Consequently, the mean prices of rice reported by farmers from villages with electricity were significantly higher, being TZS 719.5/kg (US$0.31/kg) compared to TZS 645/kg (US$0.28/kg) in villages without electricity (Isinika *et al*. 2018). Note that all these figures reflect sales within two-three months after harvest.

On use of inputs, there is no significant difference between farmers who used purchased seed (p-value = 0.69), but differences are significantly higher for the use of pesticides, herbicides and organic manure (p-value ranging from 0.00 to 0.09). All 12 famers who used organic manure sold at least 61 percent of their harvest; most of them were SSFs and only one was a MSF. Seven of the manure users (58.3 percent) had a farm size of 2.01–5ha, which recorded the highest yield when ordered by farm size (Table 3.4). Nevertheless, the proportion of farmers using manure is very low (2.4 percent). This category is also interesting since it contains the highest proportion of SRI farmers (53.4 percent) and they account for 44.3 percent of farmers in villages with electricity, which probably raised the yield and RCI for this category. Despite 26 percent of the sample reporting to own cattle and 79 percent reporting to own some livestock, most of the farmers, especially in areas where MSFs have newly settled (Isinika and Mwajombe 2018), may see little need for use of manure since they perceive their soils to be fertile. Use of manure may also be constrained by limited availability of manure and/or access to oxcarts. Only 4.6 percent of the households in the sample owned oxcarts (Isinika *et al.* 2018). Other researchers within the study area (Isinika *et al.* 2018; Djurfeldt 2017) similarly reported that the quantities of productivity enhancing inputs are often too small to bring significant improvement in land productivity. In order to determine the conditional correlation for rice commercialisation, each household's RCI was therefore regressed against selected explanatory variables.

3.3 Determinants of RCI

Results of the regression analysis for Equations 2 (Model 1) and 3 (Model 2) are presented in Tables 3.5 and 3.6 respectively. Annex 4 presents the description of the variables and their expected signs. Both models represent a good fit for the data based on the log likelihood, pseudo R-Square and corresponding F-values for each model. The results are fairly robust across both models, and are presented to broaden understanding regarding the role of electrification and other factors on rice commercialisation in the study area. The pseudo R-Square for the models improves across columns 2, 3 and 4 in Table 3.5.

In Table 3.5, the analysis (Model 1) is developed sequentially, beginning with the electricity variable, followed by the intensification scores and the interaction terms. Then, household control variables are added in the third column and the extensification variable in the fourth column. In the first column, the coefficient for electricity is positive but insignificant – and changes signs when other variables are added. This reflects the fact that the relationship between electricity and rice commercialisation is not a direct one, as postulated when formulating the sampling frame. Rather the relationship between electrification and commercialisation is mediated by intensification, controlling for key factors such as area expansion and non-farm income. The interaction terms between electricity status and intensification score have a positive coefficient, which is significant ($p = 0.05$) when the three intensification technologies were adopted, and this is robust across columns (2, 3 and 4). Hence, the relationship between electricity and rice commercialisation depends on the intensification level attained by the farmers.

Further, we find that education of the household head, farm size and access to extension services are significantly ($p \leq 0.05$) correlated with RCI. The positive correlation for education was expected as it enables farmers to seek knowledge to improve production and the farm business. There is also a positive relation between farm size and RCI. Further, the coefficient for extension services is positive. Farmer's use of agro-chemicals, especially herbicides and pesticides and, in some cases, use of inorganic fertiliser, is correlated with higher RCI scores, as farmers likely require guidance from extension staff regarding the type and application rates, thereby scoring higher. The coefficient for MSFs (a proxy for farm expansion potential – extensification) is positive but approximately equal to zero – likely reflecting the fact that area expansion is pursued not only by MSFs but also by SSFs, especially in remote villages where land for expansion is available.

As hypothesised, increasing household size has a significant negative correlation with RCI ($p \leq 0.5$). Larger families tend to have a higher dependency ratio, hence the negative correlation with commercialisation. However, the p-values of coefficients for the age of the household head and FHHs, suggest that the effects of these variables are weak. Other studies with respect to gender (Djurfeldt *et al*. 2019) and age report that younger and male farm managers tend to perform better in terms of farm productivity and profit efficiency (Msuya *et al*. 2018).

In Model 1, the coefficient for the number of MSFs in a village is positive as expected, but statistically insignificant. Technological and knowledge spill-overs from MSFs to SSFs, which increase with the concentration of MSFs in a village, are expected to have a positive influence on rice commercialisation as long as other factors remain unchanged. Initial qualitative work found that incoming Sukuma agro-pastoralists, who comprise the majority of MSFs, had introduced animal traction practices to resident farmers (Poulton 2018). Animal traction is particularly well suited to the newly settled parts of the valley closer to the wetland in Kilombero valley. Moreover, having established themselves in these areas, the Sukuma agro-pastoralists invited relatives and friends to join them, in some cases renting land to them as SSFs.

Table 3.6 presents Model 2, where a household's distance to the nearest mill is used as a proxy for the effect of electricity on rice commercialisation. The distance to the nearest large mill captures the relationships with rice production incentives via ready access to output market opportunities. This is negative, consistent with our hypothesis that electrification is correlated with increasing rice commercialisation through various opportunities, including selling rice at a higher price and using storage facilities at installed mills in order to sell at a higher price later in the year. Farmers who have more surplus to sell would benefit more from such services.
It was expected that the arrival of electricity would stimulate non-farm activities, including income

Table 3.5 Factors influencing RCI: Model 1

Variables	(1) Electrification	(2) Interaction with intensification	(3) HH controls	(4) HH & ex-tensification controls
Electricity status	0.014 (0.037)	-0.097 (0.069)	**-0.120*** **(0.067)**	**-0.114*** **(0.066)**
Intensification score				
1		0.060 (0.044)	0.038 (0.040)	0.037 (0.045)
2		0.063 (0.054)	0.017 (0.051)	0.016 (0.053)
3		0.103 (0.114)	0.039 (0.095)	0.040 (0.102)
1.Electricity_status*1.int_score		0.122* (0.073)	0.103* (0.074)	0.105 (0.068)
1.Electricity_status*2.int_score		0.089 (0.095)	0.068 (0.094)	0.069 (0.076)
1.Electricity_status*3.int_score		0.299** (0.146)	**0.264*** **(0.120)**	**0.263**** **(0.126)**
<u>Control variables</u>				
Age of HH (dummy variable)			-0.001 (0.001)	-0.001 (0.001)
Education of HH			0.016*** (0.006)	0.016*** (0.005)
FHH			-0.032 (0.041)	-0.030 (0.044)
Household size			-0.016** (0.005)	-0.016** (0.007)
Farm size (ha)			0.014*** (0.003)	0.014*** (0.004)
Total HH non-farm income			0.000 (0.000)	0.000 (0.000)
Extension service			0.088*** (0.027)	0.089** (0.038)
Number of MSFs				0.000 (0.000)
Constant	0.584*** (0.017)	0.540*** (0.032)	0.509*** (0.077)	0.502*** (0.069)
Observations	506	506	506	506
Observations	506	506	399	399
Uncensored	440	440	440	440
Censored (left)	41	41	41	41
Censored (right)	25	25	25	25
Log likelihood	-198.85	-187.44	-159.12	-159.061
F-value	0.4	21.27	6.60	6.22
Probability > F-value	0.704	0.000	0.000	0.000
Pseudo R-Square	0.0006	0.058	0.200	0.201

Note: Table 3.5 presents results from a two-sided Tobit estimation of Model 1. Standard deviations are shown in parentheses. * Significant at 10% level ** Significant at 5% level. *** Significant at 1% level.

Table 3.6 Factors influencing RCI: Model 2

Variables	(1) Distance	(2) Control for intensification	(3) HH controls	(4) HH & ex-tensification controls
Distance to nearest large mill	**-0.008*** (0.003)**	**-0.007** (0.004)**	-0.006 (0.004)	**-0.012*** (0.003)**
Intensification score				
1		0.079* (0.043)	0.052 (0.038)	0.055 (0.038)
2		0.076 (0.055)	0.021 (0.045)	0.023 (0.043)
3		**0.222*** (0.065)**	**0.145** (0.070)**	**0.149** (0.070)**
<u>Control variables</u>				
Age of HH (dummy variable)			-0.001* (0.001)	-0.001 (0.001)
Education of HH			0.012* (0.006)	0.012** (0.006)
FHH			-0.038 (0.048)	-0.030 (0.050)
Household size			-0.017* (0.009)	-0.016* (0.009)
Farm size (ha)			0.016*** (0.004)	0.016*** (0.004)
Total HH non-farm income			0.000 (0.000)	0.000 (0.000)
Extension service			0.088*** (0.032)	0.093*** (0.033)
Number of MSFs				0.002** (0.001)
Constant	0.623*** (0.028)	0.554*** (0.040)	0.571*** (0.099)	0.540*** (0.105)
Observations	401	399	399	399
Uncensored	344	344	344	344
Censored (left)	35	35	35	35
Censored (right)	22	22	22	22
Log likelihood	-170.61	-165.93	-143.13	-141.03
F-value	4.86	4.68	5.60	5.61
Probability > F-value	0.028	0.001	0.000	0.000
Pseudo R-Square	0.015	0.042	0.173	0.185

Note: Table 3.6. presents results from a two-sided Tobit estimation of Model 2. Standard deviations are shown in parentheses. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

generated from enterprises such as shops, guest houses, mobile money services and charging mobile phones. However, *a priori*, non-farm income could have either a positive or negative influence on rice commercialisation. Increased incomes from non-farm sources could be reinvested to increase rice production for market (Djurfeldt *et al.* 2019) or, alternatively, access to income from non-farm sources could substitute income from rice marketing and so reduce the pressure to sell rice. We find no clear relationship for non-farm income and commercialisation – the coefficient is insignificant.

We observe that the coefficient for village electricity status by itself in Model 1 is negative (-0.114; p = 0.096). This may be puzzling as there is no theoretical reason why farmers in villages with electricity should be less commercialised relative to their counterparts in villages without electricity. Our interpretation is that everybody responds to electrification at different speeds, both within a village or across neighbouring villages. Electrification immediately improves milling and storage services. Both improved milling and storage lead to higher prices received by farmers when they sell rice. Farmers respond to such higher prices via intensification, area expansion or both, but it seems that area expansion response is more immediate, and is more feasible in remote villages, which are not yet electrified. Moreover, it seems that the electrification dummy is picking up some of the spill-over effects from MSFs to SSFs, that occurs primarily in villages without electricity (see Table 3.3). This finding is supported by Model 2, where the coefficient for the number of MSFs is significant, as the electrification dummy picks up similar effects.

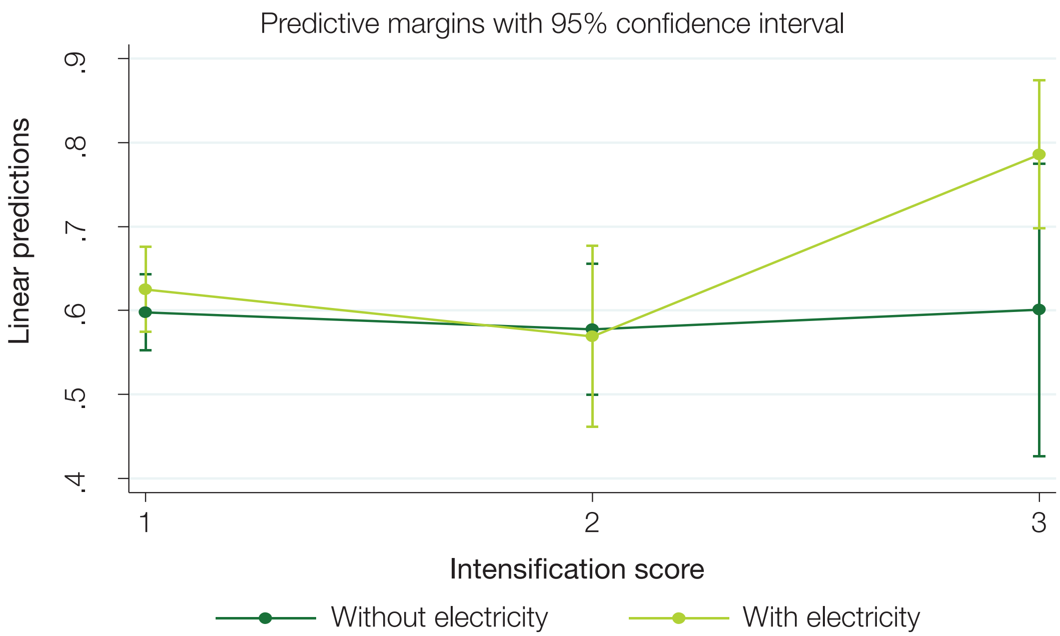
Overall, our findings are as follows: First, *farmers respond to increased market opportunities either by intensifying or extensification* in order to increase farm production. The choice will depend on the balance of factors of production (land, labour, capital, information) at their disposal. In recent years, opportunities for rice marketing have been increasing throughout Kilombero valley, but more rapidly in villages reached by electricity than in villages without. In villages reached by electricity, where land is typically scarce, a subset of farmers has successfully responded by intensifying their production. This requires, *inter alia*, some capital and some knowledge. At least some of the farmers

Table 3.7 Predictive margins for RCI: Model 1 and 2

Model 1 intensity/electricity interaction	Margin	Standard error
Score 1: without electricity	0.598	0.023
Score 1: with electricity	0.625	0.026
Score 2: without electricity	0.577	0.040
Score 2: with electricity	0.569	0.055
Score 3: without electricity	0.601	0.089
Score 3: with electricity	0.786	0.045
Model 2: Intensification score	**Margin**	**Standard error**
Score 1	0.606	0.029
Score 2	0.574	0.034
Score 3	0.700	0.054
Model 2: Distance to mill (km)		
1	0.637	0.027
2	0.625	0.024
3	0.613	0.021
4	0.602	0.019
5	0.590	0.017
6	0.578	0.016
7	0.567	0.015
8	0.555	0.015
9	0.543	0.016
10	0.531	0.017
11	0.520	0.018
12	0.508	0.021
13	0.496	0.023
14	0.485	0.025
15	0.473	0.028
16	0.461	0.031

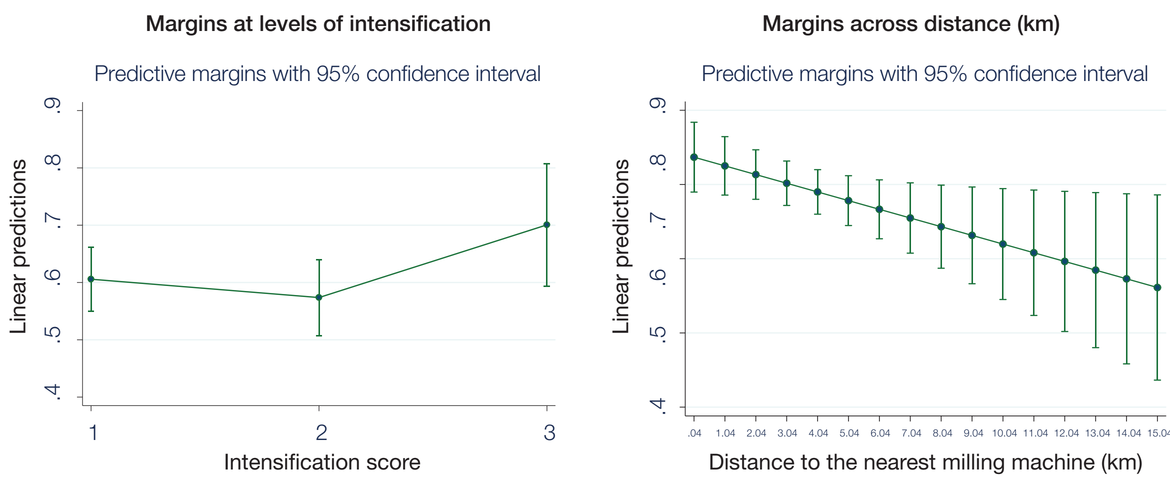
Note: Table 3.7 presents the predictive margins with standard errors from the two-sided Tobit estimations of Model 1 and Model 2.

Figure 3.6 Linear prediction intensification scores for Model 1 with 95 percent confidence interval



Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

Figure 3.7 Linear prediction intensification scores for Model 2 with 95 percent confidence interval



Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

that have engaged with the SRI programme appear to have been well positioned to respond to the increased market opportunities that have come with electrification, primarily via intensification.

Second, *in more remote villages that tend not to have received electricity yet, there has been an influx of MSFs*, who sell substantial amounts of rice to the market. This represents an extensification response to the general improvement in rice market conditions in the valley. Moreover, we hypothesise that these farmers have encouraged nearby SSFs (both existing and new) to expand their rice production, *inter alia* through the adoption of animal traction, which is presumed to be an extensification response in this context.

To examine the magnitude of marginal effects on the latent variable from our Tobit estimations, we concentrate on column 4 for both Models 1 and 2 presented in Table 3.5 and 3.6. The marginal effects are presented in Table 3.7, outlining the average marginal effect at different levels of the primary variables of interest. Holding all covariates at their respective mean, we note higher predicted RCI values at higher levels of the interaction between predicted marginal RCI values and the intensification score; and lower predicted RCI values with an increase in distance from mills.

To facilitate interpretation of marginal effects, we illustrate the predictive margins in Figure 3.6 with 95 percent confidence intervals, using: (1) Column 4 in Model 1, that visualises the change in the marginal effect by electrification status as the intensification score goes from 0 to 3; and (2) Column 4 in Model 2, that depicts the change of marginal effects by distance (kms) also with the intensification score. We note that when classifying by electrification, there is a clear jump in the marginal effect with an increase in intensification score, with the intensification response being stronger in villages with electricity. We note a similar effect when explaining RCI using distance to mills in Model 2 (Figure 3.7).

3.4 Determinants of poverty in relation to rice commercialisation

As stated earlier, the whole concern about promoting agricultural commercialisation is to foster livelihood improvements among farmers and other rural residents. Concern about reducing poverty has always been on the global agenda, especially since 1995 when the Global Summit on Social Development adopted a declaration and programme of action to eradicate absolute and reduce overall poverty (Gordon 2006). Absolute poverty is characterised by severe deprivation of basic needs including food, safe drinking water, sanitation facilities, health and education, and information. While income plays an important role in reducing poverty, access to services may also be limiting. In this study, the Multidimensional Poverty Index (MPI) of the whole sample was computed according to Santos and Alkire (2011) and the findings are presented in Table 3.8.

According to these results, the incidence of multidimensional poverty, also referred to as the headcount ratio, is 61 percent, representing the proportion of households in the sample who are multidimensionally poor. This headcount is higher than the average for Tanzania (excluding Zanzibar) at 26.4 percent, and 31.3 percent for rural areas in 2018 (World Bank Group 2019). The mean intensity of poverty is 48 percent, which means on average that the

Table 3.8 MPI across categories

Category	Incidence (%)	Intensity (%)	MPI
MPI by farmer category			
SSF	61	49	0.30
MSF	75	50	0.37
SRI	44	43	0.19
MPI by HH			
MHH	58	48	0.28
FHH	78	49	0.38
MPI by village electricity status			
With electricity	47	46	0.22
Without electricity	68	49	0.34
MPI by farm size			
< 2ha	63	49	0.31
2.01–5ha	51	47	0.24
5.01–10ha	70	52	0.37
10.01–20ha	66	49	0.32
> 20ha	79	44	0.35
MPI by RCI			
0–20	69	59	0.39
21–40	70	49	0.34
41–60	72	46	0.33
61–80	57	48	0.27
81–100	38	44	0.17
Sample	**61**	**48**	**0.29**

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

Table 3.9 MPI Scores and proportion of MPI poor farmers by category

Description	Farmer characteristic	MPI score	% households[13]		Significance of difference for % MPI poor
			MPI poor	Not deprived	
Farmer category	SSF	0.31	55.4	44.6	Chi-Square = 11.8 p = 0.001
	MSF	0.37	68.4	31.6	
	SRI	0.19	41.8	58.2	
Sex	Female	0.40	69.5	30.5	Chi-Square = 7.1 p = 0.008
	Male	0.29	50.9	49.1	
Electricity status	With electricity	0.34	44.4	55.6	Chi-Square = 11.8 p = 0.001
	Without electricity	0.34	61.3	38.7	
Farm size	< 2ha	0.32	58.5	41.5	Chi-Square = 6.3 p = 0.181
	2.10–5ha	0.24	46.9	53.1	
	5.01–10ha	0.37	62.2	37.8	
	10.01–20ha	0.32	59.1	40.9	
	> 20ha	0.35	62.5	37.5	
RCI	Sample mean	0.29	53.5	46.5	Chi-Square = 23.1 p = 0.00
	1–20	0.39	62.5	37.5	
	21–40	0.34	66.7	33.3	
	41–60	0.33	65.2	34.8	
	61–80	0.27	50.5	49.3	
	81–100	0.17	33.3	66.7	
	Sample mean	0.29	53.5	46.5	

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

multidimensionally poor households in the sample are deprived in 48 percent of the weighted indicators (listed in Annex 6). The overall MPI for the sample population (0.29) is computed as a product of the headcount and the intensity. This is higher than the mean of 0.275 for Tanzania (UNDP 2019), but lies below the cut-off point of 0.33.

Perhaps surprisingly, the MPI is highest for MSFs (0.37) and lowest for SRI farmers (0.19). The MPI also differs by village electricity status, being higher in villages without electricity (0.34) compared to those with electricity (0.22). FHHs also score a higher MPI value (0.38) compared to MHHs (0.28). Across RCI quintiles the MPI is highest for the first quintile (RCI = 0–20); a reflection of how limited land access impinges on household deprivation, especially in terms of food security.

The incidence of poverty was highest among MSFs (75 percent) and lowest for SRI farmers (44 percent), and was higher for FHHs (78 percent) than MHHs (58 percent). It was also higher for households in villages without electricity (68 percent) compared to those with electricity (47 percent). The intensity of poverty was again highest among MSFs (50 percent) and lowest among SRI members (43 percent), with little variation between SSFs and MSFs. There was also only a small difference in the intensity of poverty by sex of household head, being higher for FHHs but there was no significant difference in village electricity status (Table 3.8). Across farm size, the incidence of poverty fluctuates, being highest for farms in the range of 5.01–10 ha and consistently higher for larger farms, which is consistent with the incidence of poverty being higher for MSFs and for villages without electricity, where the majority of MSFs reside. Comparison of poverty incidence and intensity across RCI values reflects a declining trend both in terms of intensity and the overall MPI (Table 3.8).

Table 3.9 presents the MPI score in relation to the distribution of households across farmer categories. The highest proportion of households below the MPI cut-off point (0.33) was recorded among FHHs (69.5 percent) followed MSFs (68.4 percent), and was lowest for farmers in the highest RCI quintile (33.3 percent) followed by SRI farmers (41.8 percent). Also, a higher proportion of MPI farmers operate in villages without electricity, where the majority of MSFs reside. However, the distribution of MPI poor farmers by farm size does not provide a clear pattern (Chi-Square = 6.3; p = 0.181).

While MSFs attained higher RCI scores than SSFs (Table 3.1), their MPI score is lower as most live in villages that lack basic amenities such as running water. The villages are also more likely to have poor quality houses, and higher incidences of deaths in the family, either due to poor health services or households not using facilities (due to the use of alternative medicines, or traditional beliefs which mean that the sick are not taken to health services soon enough). Some of the MSFs may also be newly settled, so yet to establish permanent houses and other amenities.

The regression model (Equation 4) was developed sequentially beginning with village electricity status in the first column (Table 3.10). The model remains stable in terms of overall significance. The log likelihood-ratio increases from -277.44 to -229.26 as more variables are added, all models being highly significant ($p = 0.000$). The coefficient for electricity is negative and significant ($p \leq 0.1$), showing that households in electrified villages tend to be less MPI poor. The coefficient for the first and second RCI quintiles have positive coefficients, implying that low commercialisation levels are not associated with poverty reduction, probably because of low volumes of rice that are sold. However, the fourth and fifth quintiles have negative coefficients, implying a poverty reducing association, but all four coefficients are not significant.

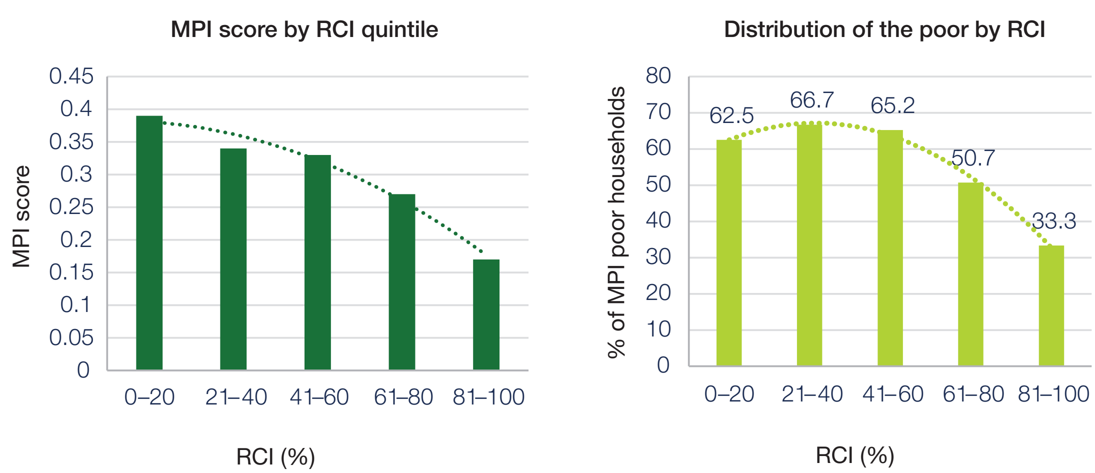
The coefficient for education of the household head is negative and significant ($p = 0.002$), which means a one-year increase in the age of the household head would reduce the probability of a household being MPI poor by 0.156 units. The coefficient for farm size is also negative ($p = 0.031$). Other variables with negative coefficients include membership of a farmer group that practices SRI, village electricity status, and RCI at the fourth and fifth quintile. However, these have a less pronounced effect on reducing poverty ($p > 0.1$)

Meanwhile, being a female household head, or having an increased age of the household head, or household size, would likely increase the MPI. Larger households tend to increase their MPI because of a higher dependency ratio (Table 3.10). Variables which have a positive association with MPI include farm size, and being an MSF. Any increase in any of these variables would tend to increase the MPI, hence higher poverty levels.

While we don't find a very strong association between RCI and MPI in some cases, there is a strong negative association between poverty and commercialisation. This implies that household poverty is strongly correlated with increasing commercialisation. We also find evidence that MSF households (especially who own relatively larger farms within the range of 10–20ha) produce and sell more rice, hence score high on RCI. But they also score high on MPI, in terms of incidence, and especially in terms of intensity (Figure 3.8). These households appear particularly deprived on health indicators including nutrition, sanitation, safe drinking water, death in the family, and also in terms of education.

The negative relationship between RCI and MPI among MSFs in Figure 3.8 tells us that most farmers in this category place a higher value on productive assets compared to assets or amenities that improve the quality of life according to global and national indicators. Different stakeholders, including community leaders and local government authorities, should conduct sensitisation campaigns to address such challenges, holding the local communities and village government accountable for things that are within their capacity, while taking up issues to be addressed by government (both by local government authorities and at central government). Factors that contribute most to poverty include poor school attendance, followed by nutrition as reported in Table 3.12. The indicator

Figure 3.8 Mean MPI and distribution of MPI poor households



Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

Table 3.10 Determinants of household poverty status: logit estimates

Variables	(1) RCI	(2) RCI and electrification	(3) HH controls	(4) SRI and MSF controls
Electrification	-0.731*** (0.206)	-0.697*** (0.213)	-0.492** (0.248)	-0.440* (0.254)
RCI quintiles				
Q2_RCI		0.074 (0.445)	0.213 (0.493)	0.210 (0.491)
Q3_RCI		0.035 (0.360)	0.330 (0.408)	0.361 (0.410)
Q4_RCI		-0.579* (0.328)	-0.154 (0.379)	-0.142 (0.382)
Q5_RCI		-1.219*** (0.368)	-0.576 (0.419)	-0.540 (0.422)
Control variables				
Age of HH (dummy variable)			0.022** (0.009)	0.023** (0.009)
Education of HH			-0.171*** (0.048)	-0.156*** (0.049)
FHH			0.966*** (0.358)	0.982*** (0.360)
Household size			0.289*** (0.060)	0.285*** (0.061)
Land size (ha)			-0.066** (0.032)	-0.090** (0.041)
SRI				-0.210 (0.309)
MSF (dummy variable)				0.501 (0.544)
Total HH non-farm income			-0.000 (0.000)	-0.000 (0.000)
Constant	0.429*** (0.129)	0.849*** (0.300)	-0.959 (0.707)	-1.037 (0.714)
Number of observations	411	411	411	411
Log likelihood	-277.44	-266.71	-230.04	-229.26
Log likelihood Chi-Square (13)	12.84	34.29	107.64	109.20
Prob > Chi-Square	0.000	0.000	0.190	0.000
Pseudo R-Square	0.023	0.060	0.190	0.192

Note: Table presents results from a logit estimation. Standard deviations are shown in parentheses. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

for asset ownership, which ranks high in the farmers' self-poverty assessment ranks lowest (seventh) among indicators of poverty, which is used by governments and development agents.

However, self-perception of poverty, measured using several subjective instruments revealed that MSFs did not perceive themselves as poor. Rather, they rated their households as richer than most villagers, or above average (Table 3.11). Only 1.4 percent of MSFs perceived their households to be poor or below average, compared to 20.4 percent among SSFs and 36.4 percent among SRI farmers. Conversely, a higher proportion of MSFs perceive their households to be rich or comfortable (52.7 percent) compared to only 25.3 percent for SSFs and 35.1 percent of SRI farmers.

Table 3.11 Farmers subjective poverty assessment

Subjective wealth status	% of respondents			Test for significance of difference
	SSF N = 277	MSF N = 57	SRI N = 77	
Subjective poverty				
Among the richest in the village	0.4	3.5	6.5	Chi-Square = 41.1 p = 0.00
Richer than most HHs	4.3	17.5	6.3	
Above average	49.8	63.3	51.9	
A little poorer than most HHs	26.4	14	23.4	
Among the poorest in village	17.8	1.4	13	
The poorest in village	2.6	0.0	0.0	
Total	100	100	100	
Subjective wealth				
	SSF **N = 349**	**MSF** **N = 74**	**SRI** **N = 106**	
Very rich	0	1.4	0	Chi-Square = 39.9 p = 0.00
Rich	1.1	8.1	9.1	
Comfortable	24.2	41.4	39.9	
Can manage to get by	41.2	3.5	13	
Destitute	0.4	0.0	0	
Total	100	100	100	

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

This positive perception among MSFs, while scoring high MPI values, may be explained by the fact that some of the factors that lead to their deprivation (poor health facilities, and access roads, electricity) are public goods, hence beyond their personal scope. But other factors that lead to their deprivation are embedded in their culture, so without sensitisation they may not consider that not having access to a toilet is a serious problem. Some MSFs are recent immigrants and have not developed permanent premises, particularly those who are renting land because whether or not they can stay in the village depend on their ability to secure land to rent for the next season.

Finally, turning to inequality within the sample population, the Lorenz curve and the corresponding Gini coefficients reflect a high degree of inequality (Annex 7). Less than 10 percent of the population

Table 3.12 Censored headcount ratio and contribution of each indicator to MPI

Dimension	Indicator	Censored headcount ratio (MPI poor population)	Weight	Contribution to overall MPI (%)	Ranking
Education	Years of education	0.08	1/6	4	6
	Child school attendance	0.36	1/6	20	1
Health	Nutrition (Food Insecurity Experience Scale)	0.30	1/6	17	2
	Mortality	0.18	1/6	10	5
Living standard	Electricity	0.60	1/18	11	4
	Water	0.22	1/18	4	6
	Sanitation	0.51	1/18	10	5
	Floor	0.50	1/18	12	3
	Cooking fuel	0.60	1/18	10	5
	Assets	0.09	1/18	2	7

Source: Authors' own, based on analysis using round one data from APRA Tanzania survey (2017)

control about 50 percent of the total household income. The distribution of non-farm income is even more squid (Annex 7) since 10 percent of the population control about 70 percent of the non-farm income, leaving only 30 percent to be shared among 90 percent of the population. The Gini coefficient for total household income is 0.65, while that of non-farm income is even higher at 0.78, varying by farmer category, sex and village electrification status. On average, a farmer from a village with electricity earns almost twice the non-farm income (TZS 1,303,985; US$566), compared to farmers in villages without electricity (TZS 656,684.5; US$285).

4 CONCLUSION

This paper assessed the effects of rice commercialisation on farmer livelihoods in Mngeta division, Kilombero district in Morogoro region, Tanzania. The study area was purposively selected within a setting where a large-scale farm (Kilombero Plantation Limited, KPL) is surrounded by numerous small-scale farmers (SSFs) and medium-scale farmers (MSFs) under the Southern Agricultural Growth Corridor of Tanzania (SAGCOT) framework. The development model being implemented in Kilombero district, as one of the six SAGCOT clusters, envisages that SSFs and MSFs will benefit directly and indirectly from having a large-scale farm in their vicinity. The expected direct benefits included technology transfer from the large farm through deliberate efforts such as SRI training, mobilisation of farmers' groups and credit facilitation. Marketing benefits were also possible if there were contractual arrangements for crop purchase. Indirect benefits were expected to accrue to everybody within the area. These most often arise when governments prioritise investment of public goods as part of prior agreements in support of a larger investor to operate in the area. With this background, this paper addressed the following questions:

- What is the level of rice commercialisation attained by different categories of farmers in the study area?
- Has rice commercialisation been inclusive?
- Has rice commercialisation resulted in different levels of livelihood outcomes? And are they inclusive?

We find that yes, commercialisation is happening in Mngeta division, a reflection of the commercialisation process in the entire Kilombero valley. On average, our sample farmers sold about 59.2 percent of the rice they produced, with a median of 65.2 percent. Larger farms are strong drivers of rice commercialisation. Higher Rice Commercialisation Index (RCI) levels also tend to be associated with land intensification in villages with electricity and farm expansion in villages without electricity, where the land is still available to enable farm expansion. For these reasons, farmers practicing System of Sustainable Rice Intensification (SRI) and MSFs scored higher RCI values. Animal drawn technology has also been a strong driver for expansion of rice farms leading to increasing rice production in the study area.

However, farm expansion comes at an environmental cost. The influx of livestock and people into Kilombero valley, especially since 2008, has been pushing rice production further back into protected wetlands. Some villages have encroached into the boundaries of Kilombero Ramsar site (Field notes during data collection 2017). Some of them have been evicted while others have been left to stay, depending on the circumstances surrounding their establishment, but this has happened at the cost of rolling back the wetland boundary. This highlights the need to strengthen institutional arrangements to monitor and coordinate the migration of humans and livestock into Mngeta division and Kilombero valley at large.

As land for farm expansion becomes exhausted, there is a need to promote productivity-enhancing technologies. Most notable among these are SRI technologies, which have been promoted by KPL and other development agents, but adoption has been low due to the perceived high cost of using improved inputs and for being labour intensive. But, SRI farmers in this study attained significantly higher mean and median yield levels. The mean yield of farmers in villages with electricity was also higher compared to farmers in villages without electricity, associated with farmers' rice intensification response. Household and farm characteristics that had a strong positive effect on RCI included education of the household head, farm size and access to extension services. Variables that had a significant negative effect included household size, village electricity status and distance to the nearest large rice mill. The latter is a cause for optimism, as electrification continues to extend through the study area. Productivity improving inputs such as inorganic fertiliser and manure and pesticides tend to increase RCI values for farmers. Consequently, there is the need to facilitate the adoption of productivity-enhancing technologies, including supporting crop breeding programmes to address the lack of improved seed and agronomic problems, such as logging when fertiliser is used, which were challenges identified during focus group discussions. Such efforts will reduce the pressure on land expansion while accelerating the commercialisation process.

A weak inverse relationship has been established between RCI and indicators of poverty. A household having a high RCI score is less likely to be 'Multidimensional Poverty Index (MPI) poor'. However, some of the farmers – especially MSFs, farmers living in villages without electricity, female famers and farmers with farm holdings less than 2ha – are more likely to be MPI poor for various reasons. MSFs face higher levels of deprivation since they live in more remote villages where access to education and health services is lower. Female-headed households scored significantly lower RCI and higher MPI scores. This calls for a specific gender focus in order to design more inclusive development programmes in future.

All of these factors have implications when designing poverty reduction strategies. Most SSFs, SRI farmers and female farmers require support to improve productivity. This can be achieved through training via government extension services and other partners in order to improve the adoption of technologies which have demonstrated a positive impact on yields.

Reducing the vulnerability of MSFs requires a dual approach: improving their productivity while also improving their performance on some of the livelihood indicators. Construction and use of improved toilets coupled with rainwater harvesting from corrugated iron roofs to improve sanitation are some of the solutions proposed. These can be implemented by individual households after awareness-raising activities are implemented.

Second, the perception of most MSFs regarding their poverty status poses a challenge, which must be addressed, especially among agro-pastoralists. The problem is reflected by subjective poverty indicators, where about 50 percent of MSFs perceive that they are living comfortably, yet they recorded the highest incidence and intensity of poverty, hence had the highest MPI score. Such problems require strategies to change the mind sets of affected communities, which may entail addressing embedded cultural constraints. Other solutions to address the high level of poverty, especially among MSFs, require investment in public goods such as roads to improve access to markets, and health and education facilities for which the government assumes a leading role, with the participation of local communities.

The SAGCOT framework envisaged that a large investor would benefit neighbouring SSFs and MSFs. The main direct impact of the large investor (KPL) in the study area could be seen through the performance of SRI farmers, who attained higher yields (rice intensification), the second highest RCI score and a significantly lower MPI score, which was almost three times lower than the highest for MSFs. However, the evidence provided by this paper is insufficient to establish a clear causal relationship between involvement in the SRI programme and these outcomes, as it has not controlled for selection bias into the SRI programme. A subsequent paper will examine this issue. The main indirect benefit of having a large-scale rice producer in the area is believed to be the improved infrastructure (road, railway and electricity), which received higher priority by the government with support from donors under the SAGCOT framework. KPL has also played a role in lobbying and advocating for or against various policy issues on behalf of all rice farmers in Tanzania. For example, farmers have always argued against food crop export bans, which have always worked against local rice producers.

This paper has argued that the influx of MSFs into the study area since 2000 has also had a significant impact on the wider trajectory of rice commercialisation in the area. Two effects are noted. Firstly, in conjunction with improved roads and the arrival of rice processing (itself facilitated by electrification), the rice surpluses produced by MSFs draw traders into the study area to buy rice. This is good for all farmers. Secondly, there appears to be technological and knowledge spill-overs from MSFs to nearby SSFs, principally focused on the use of animal traction in rice cultivation (see Table 3, Table 5 and Table 6). This has led to an extensification response to the improvement of rice marketing opportunities in those villages where land is still available, resulting in increased rice commercialisation among SSFs in these villages.

Rice commercialisation is an ongoing process in the study area, being traced as far back as the establishment of the Tanzania Zambia Railway during the 1970s. The positive outcomes of commercialisation, in terms of the rising share of rice sales, have been clearly demonstrated in this paper. Certain segments of the population, however, including women and farmers owning smaller farms (less than 2ha), face resource constraints that impede their commercialisation potential, hence attaining lower RCI levels. They also attain lower yield because they cannot afford productivity-improving technologies up to optimum levels. These farmers require additional support to raise yields in order to achieve higher commercialisation levels, thereby improving their poverty status. MSFs had the highest mean RCI score but they also recorded the highest MPI values, so had a higher probability of being 'MPI poor'. This requires the district to work in collaboration with local institutions and community members to reverse this unlikely nexus of high commercialisation in the midst of rampant poverty due to institutional and cultural constraints. Vulnerability can be reduced by using existing by-laws coupled with effective methods of raising awareness to accelerate the pace of constructing and using improved toilets, while the government works on improving water, education and health services in remote villages.

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ENDNOTES

1 Farm operations at KPL have been reduced to a minimum since 2018. The farm is currently in transition to a new investor, and is scheduled to begin operations in June 2020 (KPL farm manager, pers. comm. February 2020). Data for this paper were collected in 2017 when KPL was still operating.

2 The implementing countries are Ethiopia, Ghana, Malawi, Nigeria, Tanzania and Zimbabwe.

3 SAGCOT is a public private partnership initiative that was launched in 2010. It involves large international companies facilitating and coordinating large-scale investment in agri-processing with out-grower and contract farming components to benefit SSFs and other stakeholders around them. Originally, SAGCOT had six clusters (Kilombero valley being one of them), spread over five regions (Iringa, Mbeya, Pwani, Rukwa and Ruvuma). Some of these regions have since been split. Kilombero district lies within Kilombero valley, other districts being Ulanga, Mahenge and part of Kilosa.

4 Since 2019 KPL has ceased rice production. Future operations have not yet been disclosed to the public.

5 This activity was rescheduled to take place in early 2020.

6 RCI is used in this paper instead of the commonly-known Household Commercialisation Index due to the dominance of rice as an economic activity and the main source of income for most households in the study area.

7 The primary interview was conducted with the household head. Where the household head was a male, a second interview was also conducted with the senior female member of the household. However, this paper draws primarily from the information gathered from the interview conducted with the household head.

8 AFRINT data was collected through a panel survey covering four cross sections from 2002–2017 in nine African countries, originally involving around 4,000 households. The fourth cross section, focusing on the role of policy and institutions for equitable sustainable agricultural intensification, was conducted in Malawi, Tanzania and Zambia.

9 In the histogram in Panel B (Figure 2.1), each unique value of RCI has its own bar, with frequency on the y-axis, rather than the density. The spike on the far left and the right of the histogram are the bars for cases where RCI = 0 and RCI = 100. The height of these bars relative to all the others clearly shows the excess number of cases with these values.

10 In presenting our results, the role of the government to improve infrastructure according to the SAGCOT framework is not assessed directly. Rather it will be assessed in a temporal perspective after the second wave of data collection to assess whether there are improvements in road, communication and electrification infrastructure over time. Panel data will also assess changes of commercialisation pathways and corresponding livelihood impacts.

11 These figures are based in part on anticipated future sales that were reported by respondents and in part on estimated future sales where this question was not asked for one or more plots (see section 2.2.1).

12 The presence of electricity in a village is the single biggest determinant of distance to a large mill. However, there is also substantial difference in distance to a mill within some of the more dispersed villages.13 These represent percent of households within the sample, which are below the MPI cut-off point of 0.33 and those which are not.

APPENDICES

Appendix 1 Composition of the final sample of farmer by gender and farmer category

Category of farm households	MHH	FHH	Total	
	N	N	N	%
SSF	471	54	357	66.5
MSF	72	2	74	13.8
SRI farmer	96	10	106	19.7
Total	**471**	**66**	**537**	**100**

Appendix 2 Composition of the final sample used for computation of RCI and MPI

Category of farm households	MHH	FHH	Total	
	N	N	N	%
SSF	280	50	330	65.2
MSF	71	2	73	14.4
SRI farmer	93	10	103	20.4
Total	**444**	**62**	**506**	**100**

Appendix 3 RCI by quintile and farmer category

Quintile by RCI (%)	SSF N = 330	RCI of MSFs N = 68	SRI farmer N = 102	Sample total N = 495
0	10.0	2.7	5.8	8.1
1–20	6.7	2.7	3.9	5.5
21– 40	10.3	9.6	3.9	8.9
41–60	23.6	15.1	17.5	21.1
61–80	31.5	46.6	33.0	34.0
81–100	17.9	23.3	35.9	22.3
Total	**100**	**100**	**100**	**100**

Appendix 4 Commercialisation level by different farmer categories

Category	Farmer characteristic	Lowest 1–40 Q1–Q2	Middle 41–60 Q3	Highest 61–100 Q4–Q5	Total (%) commercialised 1–100 Q1–Q5	Significance of Chi-Square and p-value
Farmer category	SSF	27	23.6	49.4	90	Chi-Square = 29.106 p-value = 0.001
	MSF	12.3	15.1	69.9	97.3	
	SRI	13.6	17.5	68.9	91.9	
Sex	Male	13.5	20.5	58.1	92.1	Chi-Square = 9.083 p-value = 0.106
	Female	20.9	25.8	43.6	90.3	
Farm holdings (ha)	< 2	19	27	41	86.9	Chi-Square = 47.834 p-value = 0.000
	2.1–5	11.3	17	66.5	94.8	
	5.1–10	11.3	18.9	66	96.2	
	10.1–20	11.5	11.5	76.9	100	
	> 20	0	9.1	90.9	100	
Infrastructure	Yes electricity	12.8	18.6	58.6	90	Chi-Square = 11.4 p-value = 0.044
	No electricity	15.5	23	54.7	93.2	
	Yes all weather road	13.8	21.7	56.3	91.8	Chi-Square = 1.981 p-value = 0.852
	No all weather road	18.3	28	56.3	92.3	
Use of various inputs	No purchased seed	13.9	22.1	56.6	92.6	Chi-Square = 3.065 p-value = 0.69
	Yes purchased seed	15.5	18.2	55.4	91.9	
	No artificial fertiliser	14.2	23.3	53	90.5	Chi-Square = 27.692 P-value = 0.000
	Yes artificial fertiliser	14.9	9.5	75.7	100	
	No organic manure	14.6	21.7	55.3	91.7	Chi-Square = 9.555 p-value = 0.089
	Yes organic manure	0	0	100	100	
	No pesticides	16.6	23.5	47.9	88.3	Chi-Square = 12.739 p-value = 0.026
	Yes pesticides	12.6	19.8	61.7	94.2	
Tillage services	Did not use tillage service (animal drawn technology or tractor)	17	13.2	39.6	69.8	Chi-Square = 42.506 p-value = 0.000
	Used tillage service	13.9	22.2	58.3	94.5	
	No access to tractor	11.3	17.7	56.5	85.5	Chi-Square = 10.606 p-value = 0.06
	Have access to tractor	15.5	22.3	56.3	94	
Other services	No extension service	31.5	22.3	50.6	89	Chi-Square = 16.109 p-value = 0.007
	Yes extension service	28.2	12.1	63.7	95.5	
	No agro-dealer service	12.2	18.9	59.4	90.6	Chi-Square = 3.253 p-value = 0.661
	Yes agro-dealer service	15.6	22.4	54.6	91.9	
	No mobile money	20.5	17.9	46.5	91.9	Chi-Square = 19.172 p-value = 0.002
	Yes mobile money	12.5	22.2	59.2	93.9	
Farm assets	No ox-cart	14.3	21	56	91.7	Chi-Square = 8.762 p-value = 0.119
	Yes ox-cart	17.4	26.1	56.5	100	
	No plough/harrow	14.9	20	55.7	90.7	Chi-Square = 6.708 p-value = 0.243
	Yes plough/harrow	12.6	25.3	60	97.9	
	No livestock	10.5	16.2	55.3	81.9	Chi-Square = 28.504 p-value = 0.000
	Yes livestock	15.8	23	55.8	94.6	
	No cattle	15.2	19.7	54.9	89.9	Chi-Square = 16.461 p-value = 0.006
	Yes cattle	12.4	25.6	59.7	97.7	

Appendix 5 List of variables for estimating determinants of the RCI

Variable	Specification	Expected sign
Age of household head (HH attribute)	Years	positive or negative
Level of education of of household head (HH attribute)	Years of formal education	positive
Sex of household head (HH attribute)	Coded as a dummy – assigned a value of 1 if HH is a female and 0 if HH is a male	negative
Household size (HH attribute)	Number of household members	negative
Plot size (HH attribute)	Total holding size hectares	positive
Access to extension services (HH attribute)	Coded as a dummy – assigned a value of 1 if a farmer had access to extension services and 0 otherwise	positive: In this model, used as a HH attribute since, famers' access to extension services is limited by availability of staff. SRI members, MHHs and famers in villages with electricity having more access
Total HH non-farm income	Value of total non-farm income earned by the household	positive
Distance to nearest mill (market access attribute)	Radial distance from the household to the nearest large rice mill, calculated using GPS coordinates (in km)	negative
Electricity status (village attribute)	Coded as dummy – assigned a value of 1 if a village is connected and 0 if not connected	positive: Electricity connection promotes establishment of rice mills and other electricity-based commercial activities, providing incentives for rice commercialisation
Intensification score (HH attribute)	Defined as a sum of scores associated with use (1) and non-use (0), of yield increasing inputs or services (purchased seed), chemical fertiliser, organic fertiliser, and pesticides. Minimum score 0 and maximum score 6 Score 1 = 1 technology adopted Score 2 = 2 technologies adopted Score 3 = 3 technologies adopted Score 4 ≥ 4 technologies adopted	positive
Electricity*intensification interaction	Intensification score X village electricity status	positive
Number of MSFs in a village	Number of MSFs in a village, derived from initial construction of survey sampling frame	positive: More MSFs are found in villages where there is land for expansion. Their presence is expected to have a positive effect on rice commercialisation through a larger volume of marketed surplus

Appendix 6 List of variables for estimating determinants of MPI

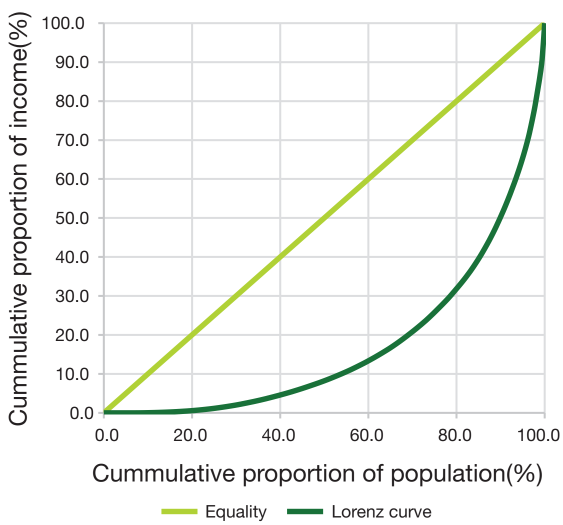
Variable	Definition	Expected sign
Age of HH head (dummy)	Age of household head in years	positive
Education of HH head	Year of schooling for household head	negative
FHH	Sex of household head: 1 if female, 0 if male	positive
Household size	Number of people in a household	positive
% of land under rice	Total area of farm plots in hectares	negative
Total HH non-farm income	Value of total non-farm income earned by the HH	negative
Electricity status	1 if village has electricity, 0 otherwise	negative
SRI dummy	1 if farmer practices SRI, 0 otherwise	negative
MSF dummy	1 if farmer is a MSF, 0 otherwise	negative
RCI	Used as a continuous variable	negative
RCI Q1	1if famer belongs to quintile 1, 0 otherwise	negative
RCI Q2	1if famer belongs to quintile 2, 0 otherwise	negative
RCI Q3	1if famer belongs to quintile 3, 0 otherwise	negative
RCI Q4	1if famer belongs to quintile 4, 0 otherwise	negative
RCI Q4	1if famer belongs to quintile 5, 0 otherwise	negative

Appendix 7 Factors used to construct various indices and aggregated variables

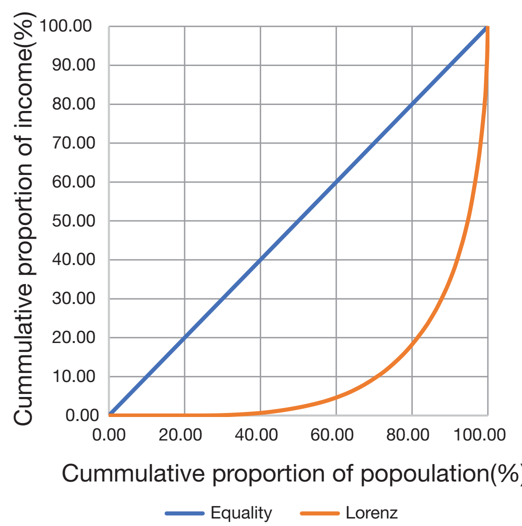
Variable	Variable used
HCI for paddy	i. **Quantity of harvested rice** ii. **Quantity of sold paddy**
Price per kilo of paddy	i. **Sales value in Tanzania Shillings** ii. **Quantity of sold paddy**
MPI	i. **Years of schooling** (given 1 for a household that did not have any member who has at least five years of schooling) ii. **School attendance** (given 1 for a school-age child out of school, and 0 otherwise). iii. **Child mortality** (given 1 for a household that reported a death of a child in the household during the past ten years, and 0 for a household that had not). iv. **Nutrition** (used the Food Insecurity Experience Scale with a cut-off point of five, where those scoring five and above out of nine were considered to be deprived nutritionally). v. **Living standards:** - **Electricity** (given 1 for a household that did not have electricity, and 0 for one that had electricity). - **Drinking water** (given 1 for a household that did not have access to clean water, i.e. use unprotected sources, and 0 for a household that had access to clean drinking water). - **Sanitation** (given 1 for a household that did not have adequate sanitation (i.e. no toilet facility, go to bush or field, use pan or bucket, use traditional pit latrine), and 0 for a household that had a ventilated improved pit latrine and a flush toilet). - **Flooring** (given 1 for a household that had dirty, earth, dung floor etc, and 0 to a household that had a tiled, cemented, concrete floor). - **Cooking fuel** (given 1 for a household that cooked with wood, charcoal or dung, and 0 was given to a household that used gas, electricity or paraffin as the main source of cooking energy). - **Asset ownership** (given 1 for a household that did not own did not own a car or tractor, or more than one of the following: radio, TV, telephone, bicycle, motorcycle, or refrigerator; the value of 0 was given to a household that owned more than one of the listed assets).

Minimum dietary diversity index for woman of reproductive age	i. **A dichotomous indicator was made (in which for the women who** consumed at least five out of twenty defined food groups was given a value of 1, and for the woman who consumed less than five food groups was given a value of 0).
Food security	i. **A dichotomous indicator was used** to define food secure and food insecure households. A value of 1 was given for a household which was considered to be food secure, and a value of 0 was given for a household which was considered to be food insecure. A household which experienced five or more defined food insecurity situations out of nine was considered to be food insecure, while those which faced less than five were considered to be food secure.
Subjective poverty	**Ladder steps, those below cut-off were given the value 1 and those above a value of 0**

Appendix 8 Lorenz curves for total household income and non-farm income



Appendix 8 (a) Lorenz curve for total household income: Mngeta division, Kilombero district



Appendix 8 (b) Lorenz curve for non-farm income: Mngeta division, Kilombero district

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