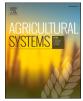
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Pathways toward inclusive low-emission dairy development in Tanzania: Producer heterogeneity and implications for intervention design

E.M Kihoro^{a,b,*}, G.C. Schoneveld^c, T.A. Crane^a

^a International Livestock Research Institute, Nairobi, Kenya

^b Wageningen University and Research, Wageningen, the Netherlands

^c Centre for International Forestry Research, Nairobi, Kenya

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ABSTRACT

Context: Reducing greenhouse gas (GHG) emissions from the agriculture sector – especially livestock – through low-emission development (LED) has attracted increased global attention. However, producers rarely prioritize emission reduction in their day-to-day practices, resulting in a mismatch between global and national environmental policies and local development interests. This raises the urgency of identifying overlapping solution spaces that would address global and national environmental targets and farmers' production goals. *Objective:* The objective of this study is to identify pathways for scaling LED that better account for divergent

Objective: The objective of this study is to identify pathways for scaling LED that better account for divergent smallholder capabilities, strategies, and interests.

Methods: A multivariate cluster analysis was used to evaluate producer heterogeneity. The analysis utilized data from 1176 household surveys in Tanzania. Informed by these results, stakeholder workshops were held to identify how each group is uniquely constrained in the adoption of LED practices and viable paths forward.

Results and discussions: Our results reveal six distinct farmer types, distinguishable by their asset base, livestock ownership, cattle breeds, access to market, and income diversity. The six groups presented three levels of LED uptake, high, moderate, and low. Variants of technological packages and market-based interventions, access to better quality inputs, and extension services will be more impactful when correctly matched to producers' asset portfolios, interests, and needs for the high and moderately intensifying producers. However, interventions that address both the knowledge and resource gaps for producers who demonstrate low uptake of LED will be more appropriate. Achieving GHG reduction will be modest from already intensifying groups and the low uptake groups, while moderately intensifying groups present the highest leverage for increased GHG reduction potential. This highlights how taking a food system approach rather than a technological package would be more beneficial especially in targeting groups that are not interested in LED.

Significance: This study challenges the conceptualization of LED as a simple technological fix. We demonstrate that LED, as currently conceptualized, is not equally accessible or appealing to everyone. Consequently, successful LED uptake is contingent on donor and state ability to match LED strategies, local development priorities, and food systems objectives to develop more targeted needs-driven implementation pathways.

1. Introduction

The potential to mitigate greenhouse gas (GHG) emissions in the agricultural sector is increasingly recognized in global environmental policy (Lipper, 2014; Thornton and Herrero, 2010). The livestock sector is often seen as a promising avenue for reducing GHG emission intensities because it accounts for 65% of global agricultural GHG emissions (Thornton and Herrero, 2010; Tubiello et al., 2014). Achieving this reduction involves increasing consumable outputs per unit of GHG

emission through productivity and efficiency enhancements (Havlík et al., 2014; Herrero et al., 2016). However, smallholder farmers' management priorities rarely account for GHG emissions. Instead, smallholders' livestock keeping practices are driven by a variety of objectives, including profit, but also other economic and social considerations (Weiler et al., 2014). Still, farmer and low-emission development (LED) priorities are not irreconcilable because emission reduction need not result in economic compromise (Havlík et al., 2014). The adoption of more intensive production practices consistent with LED generally helps

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^{*} Corresponding author at: P.O BOX 30709, Nairobi 00100, Kenya. E-mail addresses: E.Kihoro@cgiar.org, emkihoro@gmail.com (E.M Kihoro).

raise agricultural productivity (ibid). Such practices can therefore both increase producer incomes and reduce GHG emissions per unit of production (Herrero et al., 2016; Thornton and Herrero, 2010).

For the livestock sector, so-called triple-win LED outcomes can be achieved through productivity gains, improved profitability, and reduced GHG emissions intensities. However, LED often remains an overarching goal that lacks clear implementation strategies and does not always correspond with local interests and priorities (Garnett et al., 2013). The typical mismatch between global and national environmental policy and rural development priorities thus raises the need to identify possible solution spaces (Michalscheck et al., 2018; Ollenburger et al., 2018), where global and national environmental targets overlap with farmers' production goals, capabilities, and ambitions. In practice, many LED strategies focus on technical fixes but fail to adequately account for the socio-institutional dimensions of production and distribution that shape uptake of proposed technologies (Herrero et al., 2016; Taylor, 2018).

Technocentric approaches to LED have several limitations. Firstly, most technocentric LED interventions take a "one-size-fits-all" approach to extension support, failing to appreciate how farmer heterogeneity affects the implementation of new practices. Secondly, technocentric LED interventions tend to be designed around the assumption that intensification and productivity gains produce socio-economic co-benefits for all producers. This assumption ignores the fact that returns from intensification do not necessarily meet the financial and social interests of all producers equally. The benefits derived from and costs associated with intensification are often unevenly distributed across social classes and categories (Tavenner et al., 2019). To ameliorate the distributional risks associated with technocratic approaches, many scholars have recently begun to explore methodological and analytical approaches that help to account for the diversity of farmers and adoption constraints (Kuivanen et al., 2016; Verkaart et al., 2018; Schoneveld et al., 2019).

The objective of this study is to identify pathways for scaling LED that better account for divergent smallholder capabilities, strategies, and interests. With donor and government LED investments in the livestock sector on the rise, more deliberate consideration of farmer differentiation is an essential first step to anticipating the diverse socioeconomic determinants of adoption and programmatic success. Most empirical studies rely on regression analyses to identify factors that influence adoption rates (Prokopy et al., 2008). Such studies however rarely capture how barriers to adoption vary across different producer groups and across space. By homogenizing farmers, they consequently often suffer from a composition problem by not accounting for diversity. This raises very real questions about the policy relevance of many extant adoption studies. This study aims to advance our understanding of differentiated adoption barriers through the development of a typology of dairy farmers. We use this typology to examine how adoption rates of key LED practices differ across producer groups and identify adoption barriers unique to each group. We do this using a three-staged approach. First, we analyze farmer heterogeneity using a multivariate cluster analysis that draws exclusively on socio-economic variables. Second, we analyze the extent to which farmers in the different clusters have thus far adopted different LED practices. Third, we analyze what constrains and incentivizes the adoption of LED practices within each group. This approach is designed to facilitate the identification of more targeted and actor-disaggregated intervention strategies and LED policies.

In doing so, this article not only produces knowledge that is more relevant to LED policy-making, but also advances the literature on smallholder heterogeneity (Alvarez et al., 2018; Dorward et al., 2009; Tittonell et al., 2015) and LED in smallholder livestock systems (Paul et al., 2021; Ndung'u et al., 2019; Ericksen and Crane, 2018; Herrero et al., 2016). Although a small number of studies have previously explored the relationship between farmer heterogeneity and intervention designs (e.g. Schoneveld et al., 2019; Verkaart et al., 2018), this article is, to our knowledge, the first attempt to explore the interface between farmer heterogeneity and LED. While results reveal how smallholder barriers to uptake of LED practices do indeed differ profoundly across farmer sub-groups, they also point to several structural adoption barriers that may undermine the efficacy of LED interventions more generally. We also show that some sub-groups are easier to target for 'quick wins', while others will require more long-term support. This article finally explores how LED interventions can become more impactful by anticipating farmer heterogeneity and adopting a food systems perspective.

2. Background

2.1. Smallholder transformation

Uptake of LED in the agriculture sectors necessarily demands a transformation of existing production systems. Such transformations demand change both at the institutional and societal levels (Hebinck et al., 2018). Transformation involves "changes in structural, functional, relational, and cognitive aspects of socio-technical-ecological systems that lead to new outcomes" (Patterson et al., 2017, p. 2). This emphasizes a societal change beyond mere technocentric solutions (Geels, 2002). Technocratic approaches to agricultural transformation have been widely criticized because they fail to capture the dynamism and contingencies of development, including social differentiation and local institutional frameworks surrounding transformation and sustainability (Abrol, 2005; Berkhout et al., 2005; Leach et al., 2010).

Various conceptual approaches have been employed to analyze societal transformation processes (see Patterson et al., 2017, for more details). This study follows the transformative pathways to sustainability approach developed by Leach et al. (2010), which depicts transformation as a process that is transitional and continuously shaped by social feedback, as well as by varying spatial and structural contexts (Leach et al., 2010; Lindahl et al., 2016). It emphasizes that transformation is political, complex, dynamic, and involves questioning dominant narratives (Leach et al., 2010). Consequently, no single transformation pathway can fit all situations. Presuming homogeneity of actors within a system is therefore ill-advised (Leach et al., 2010; Stringer et al., 2020). This implies that multiple narratives of change coexist within systems, with successful transformations typically involving diverse 'pathways' for different individuals (Scoones et al., 2020).

We use the pathways approach to understand how different farmers' interactions with various structural and institutional conditions differentiate the uptake of LED practices. While households differ in their motivations, strategies, socio-economic characteristics, and ability to access productive resources such as land, labour, and inputs, they are also confronted with trade-offs concerning resource (re)allocation and production decisions (Salmon et al., 2018). For instance, in areas with productive and significant grazing lands, the urgency of on-farm fodder production is reduced (Clay and King, 2019). Vast distances from the homestead, where cows are kept, to households' fields can make the cutand-carry fodder grass production extremely labour-intensive. It is easier to intensify in the higher altitude conditions, where households have access to smaller pieces of land, reside in closer proximity to their farms and lower temperatures support the rearing of crossbred cows. On the other hand, keeping fewer crossbred cows might be more difficult in lower, more arid regions dominated by pastoralists who keep large numbers of local cattle both for economic and cultural reasons. This highlights how household uptake of LED practices is highly contextspecific (Clay and King, 2019). Weak or oversimplified understanding of the local processes that shape the viability of alternative transformation pathways may lead to the development of unsuitable interventions that target the wrong farmers with the wrong technologies. It may also exacerbate processes of social differentiation and entrench existing inequalities when interventions inadvertently privilege better resourced and capacitated farmers.

2.2. Conceptualising smallholder heterogeneity and implications to LED

Although the broader pathways approach explains transformation broadly, it is yet to be comprehensively operationalised. To further our understanding of farmer heterogeneity, we, therefore, look elsewhere, drawing particularly on the framework from Dorward et al. (2009). The framework is based on the simple supposition that households aspire to retain and/or advance their current wellbeing. Dorward proposes three distinct household strategies: "hanging in," "stepping up" and "stepping out." As others have shown, unpacking such strategies can make valuable contributions to explaining smallholder adoption behaviours (Schoneveld et al., 2019; Verkaart et al., 2018). Households "hanging in" are constrained and less likely to innovate on their agriculture activities to minimize risk and maintain their current livelihood level. Households that are "stepping up" can invest resources in existing agricultural activities; often motivated to accumulate assets through productivity enhancements. Finally, households that are "stepping out" are accumulating and diversifying into non-farm livelihood activities; often to transition out of agriculture (Dorward et al., 2009). Over the years, additional strategies not captured by Dorward et al. (2009) have been proposed. Schoneveld et al. (2019), for example, show that increasingly more urbanized households are "moving through" (e.g. entering agriculture for more speculative purposes, before moving out), while some households are "moving in". These are generally new entrants to agriculture, often using non-farm income to invest in agriculture in response to a specific opportunity in the sector.

Accounting for such strategies helps development practitioners depart from "one-size-fits-all" approaches (Alvarez et al., 2018; Schoneveld et al., 2019; Thornton et al., 2018; Tittonell, 2014). For example, farmers "stepping up" are more inclined to respond to market-based interventions that provide offtake guarantees, while farmers "hanging in" often particularly benefit from capacity building activities (Verkaart et al., 2018). Such approaches are increasingly gaining traction in the donor community in recognition of the sub-optimal results produced by "one-size-fits-all" approaches (see, for example, DFID, 2015). That said, while the strategies proposed by Dorward et al. (2009) and others are a useful heuristic for interpreting farmer heterogeneity, farmer strategies are not our entry-point. Instead, we use Dorward et al. (2009) framework to help interpret results from a more data-driven farmer typology development approach that does not attempt to identify the strategies ex-ante, but rather inductively by examining key strategy constructs. This includes livelihood activities, capabilities, and assets (Dorward et al., 2009; Ellis, 1998). It, therefore, enables us to identify additional or variations of previously identified strategies that are unique to the dairy sector, Tanzania, and/or LED.

3. Methodology

3.1. National context and study sites

The study was conducted in Tanzania, selected for its dairy production potential, large milk productivity gap, national milk deficit, and per capita consumption gap (Katjiuongua and Nelgen, 2014; Nell et al., 2014). Tanzania has the third-largest cattle herd in Africa, and the Tanzanian government has identified dairy as a priority growth sector in its Livestock Master Plan (Michael et al., 2018). However, the country experiences a structural milk deficit and is consequently a net importer of dairy products (Nell et al., 2014). In Tanzania, the livestock sector contributes 13% to agricultural gross domestic product (GDP) and 5.9% to national GDP (Makoni et al., 2014). Approximately one-third of the livestock sector's contribution to GDP comes from the dairy sector (TDB, 2018). With Tanzanians on average consuming only 45 l of milk per year (TDB, 2018), much of the Tanzanian population consumes a fraction of FAO's recommended 200 l per annum (Nell et al., 2014). Milk predominantly originates from comparatively unproductive local cattle breeds, which account for 70% of the total national milk production,

generally kept within pastoral and semi-intensive production systems (Michael et al., 2018).

Even though the sector's contribution to rural development is wellrecognized, it is increasingly attracting attention for its high GHG emission intensities (FAO, 2019). Based on Tanzania's Nationally Determined Contribution (NDC), the country seeks to reduce its GHG emissions by between 10 and 20% by 2030 over the business as usual scenario (The United Republic of Tanzania, 2015a). Emissions from livestock account for approximately 72.5% of Tanzania's total emissions from the agricultural sector (Irish, 2018, p. 12). This is slightly higher than the global average of 65% (Tubiello et al., 2014). In Tanzania, milk production from the dairy sector emits approximately 28.8 million tons of carbon dioxide (CO₂) equivalent (eq.) (FAO, 2019). A study conducted by FAO (2019) in Tanzania noted that "the GHG profile of milk is dominated by methane 95.5 %, while the nitrous oxide (N2O) and (CO₂) contribute 4.2 % and 0.3 % of the total emissions, respectively" (FAO, 2019, p. 9). The average national emission intensity for milk is 19.9 kg CO₂ eq./kg Fat and Protein Corrected Milk (FPCM) (FAO, 2019). Previous research has shown that technical interventions have the potential to increase milk production by 29% for improved systems, while reducing GHG emissions by 46% (ibid). Because of their low degree of intensification, traditional dairy production systems have the potential to increase milk output by 56% and decrease emission intensities by 54% (FAO, 2019).

Research activities were performed across four districts and provinces, namely Mvomero district in the Morogoro region, Mufindi district in the Iringa region, Njombe district in the Njombe region, and Rungwe district in the Mbeya region (Fig. 1).

These sites were selected based on their distinctive biophysical and social conditions; thereby ensuring that a diversity of geographies and production systems representative of Tanzania are captured. The salient characteristics of the four districts are summarized in Table 1. Mvomero has a mixture of pastoralists and mixed crop farmers, representing a range of systems from extensive grazing to intensive dairy (The United Republic of Tanzania, 2018). No major processors collect milk directly from producers from this district. Mufindi's livestock keepers mainly keep their cattle within semi-intensive systems, and the milk market is poorly developed due to seasonal milk deficits. Most of the milk is therefore marketed locally (The United Republic of Tanzania, 2015b). Most households prioritize crop production, with cows primarily functioning as a source of traction and manure. Njombe, in contrast, has experienced decades of dairy development interventions (The United Republic of Tanzania, 2016). This produced numerous dynamic dairy farmer organizations and both commercial and community co-owned milk processing plants. Finally, Rungwe is characterized by highly commercial and competitive milk markets, with almost every household owning a cow (The United Republic of Tanzania, 2015c). The district has a large milk surplus, with many milk buyers, both formal and informal, and commercial processors collecting milk. (See Table 2.)

3.2. Sampling

We sampled households using a two-stage approach. In the first stage, biophysical clusters were developed to ensure that variability in production systems not only across but also within districts were sufficiently captured and accounted for. The second stage entailed a random selection of respondents within villages representative of each of the biophysical clusters identified under the first stage.

3.2.1. District and village sampling

The development of biophysical clusters involved cluster analysis using the k-means algorithm (Hartigan and Wong, 1979). Cluster analysis was performed using spatially explicit data on rainfall, temperature, and elevation. These variables are known to shape dairy farming suitability and systems (e.g. Jesse et al., 2020). To identify the appropriate number of clusters per district, the "natural breaks" feature on QGIS was

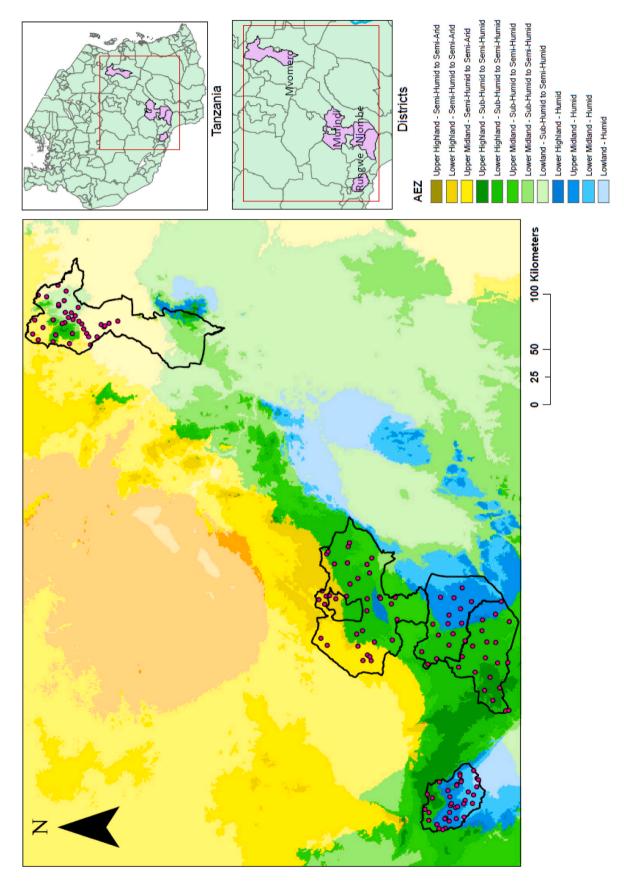


Fig. 1. Tanzania study sites.

Table 1

Characteristics of each of the four districts.

Characteristic	Unit	Rungwe	Njombe	Mufindi	Mvomero
Area	Km ²	2,078	6,366	7,123	7,325
Population	Persons	339,157	216,010	317,731	312,109
Population density	Persons/ km ²	163	34	45	43
Indigenous cattle	Number	22,804	59,195	81,162	65,064
Crossbred cattle	Number	55,337	7784	6140	1923
Grazing land	Area in ha	0 ha	32,824 ha	66,223	15,620 ha
Livestock production systems	From most to least frequent	Intensive semi- intensive	Intensive Extensive	Semi- intensive Extensive	Extensive systems Semi- intensive

Source: District socio-economic profiles: Mufindi (The United Republic of Tanzania, 2013), Mvomero (The United Republic of Tanzania, 2018), Njombe (The United Republic of Tanzania, 2014, The United Republic of Tanzania, 2013), Rungwe (The United Republic of Tanzania, 2015, 2015d).

used. This yielded a three-cluster solution with high between-cluster variability and low within-cluster variability. The three clusters comprise low (high temperature, low rainfall, and elevation), medium (ranked moderately on all the parameters), and high (low temperature, high rainfall, and elevation) suitability (Fig. 2).

Villages were sampled by distributing 36 points across the three clusters in each of the four districts. The village closest to a given point was selected for inclusion in the sample. Point assignment to each cluster depended on cluster area (e.g. more points were placed in larger clusters). This stratified sampling approach sought to ensure population representativeness, as well as to capture socio-economic variation across space.

3.2.2. Household sampling

In the selected villages, a sampling frame was constructed, with the help of village elders, which captured all households owning an adult cow producing milk or an in-calf heifer. The sample size was estimated following the Yamane (1967) formula later applied by Israel (2003) and Kihoro (2016), which is used when the population size is known.

$$n = \frac{N}{1 + N(e^2)}$$

where n = sample size, N = total (targeted) population, and e is the confidence level (5%). For instance, in Rungwe, the total number of households with a cow was 1425, which resulted in a sample size of 312, this was rounded off to 350 to accommodate outliers or data quality issues. A total of 350 households with a cow were randomly selected in

Table 2	
Characteristics of each cluster within the fo	ur districts.

Rungwe and Njombe and 250 in Mvomero and Mufindi, as these districts also had fewer households keeping cows. A total of 1200 households were surveyed in the four districts using a structured questionnaire.

3.3. Data collection

This research was performed under the IFAD-funded project entitled "Greening Livestock: Incentive-based Interventions for Reducing the Climate Impact of Livestock in East Africa". Data was collected using a household survey instrument that was loosely based on the Rural Household Multi-Indicator Survey (RHOMIS) (Hammond et al., 2017). Our instrument captured the following types of data: (1) household demographic characteristics; (2) household assets; (3) livelihood portfolio; (4) management practices; (5) milk marketing practices; and (6) producer perceptions on climate change and the impacts of dairy to the environment. Data were collected between December 2017 and June 2018 during the wet season across all study sites. A total of 1200 households were surveyed. However, after data cleaning and removal of outliers, results from 1176 households were retained for the cluster analysis: 350 from Rungwe, 343 from Njombe, 240 from Mvomero, and 243 from Mufindi.

3.4. Analytical framework

The following sections describe our three-staged analytical framework, following the three steps outlined in the introduction.

3.4.1. Developing farmers typologies

A quantitative data-driven approach to developing farmer typologies was employed, complemented by participatory validation workshops (see Section 3.4.3 for more information). As discussed above, the farmer typology was developed using only socio-economic data, such as assets, capabilities, and income sources. This methodology departs from many farm systems approaches (Kuivanen et al., 2016), which combine both farmer characteristics, farm characteristics, and farming activities. By not combining practices and farmer characteristics, one is better able to explore the relationship between the two and how these are influenced by confounding factors (Schoneveld et al., 2019).

A multivariate cluster analysis was using the DAISY package in R (3.5.1). DAISY uses Gower distance and partitioning around medoids (PAM) to produce clusters that have the greatest within-group similarity and greatest dissimilarity between groups. Because the survey data comprised of mixed data types (continuous, categorical, binary), k-means classification would not be appropriate for this analysis. To obtain appropriate cluster numbers, silhouette width from PAM and dendrograms were used (Mooi and Sarstedt, 2010). We did not conduct a principal component analysis (PCA) prior to the cluster analysis to preserve the data structure.

A total of 18 socioeconomic variables were used for the clustering

District	Cluster	% area	Number of points	Temperature [°C]	Altitude [Meters]	Rainfall [mm]
Rungwe	Low	33	12	20.6-24.5	498-1134	900-1270
Rungwe	Mid	42	15	16.9-20.6	1134–1794	1270-1670
Rungwe	High	25	9	11.6-16.9	1794–2760	1670-2070
Mvomero	Low	8	3	23.0-27.0	200–700	600-800
Mvomero	Mid	22	8	19.0-23.0	700-1300	800-1000
Mvomero	High	69	25	12.0–19.0	1300-2900	1000-1500
Mufindi	Low	25	9	19.2–22.8	800-1400	620-840
Mufindi	Mid	33	12	17.6–19.2	1400-1700	840-1060
Mufindi	High	42	15	15.9–17.6	1700-2100	1060-1410
Njombe	Low	17	6	19.7–23	442-1533	1280-1480
Njombe	Mid	61	22	16.5–19.7	1534–1733	1120-1280
Njombe	High	22	8	13.3–16.5	1733-2491	900-1120

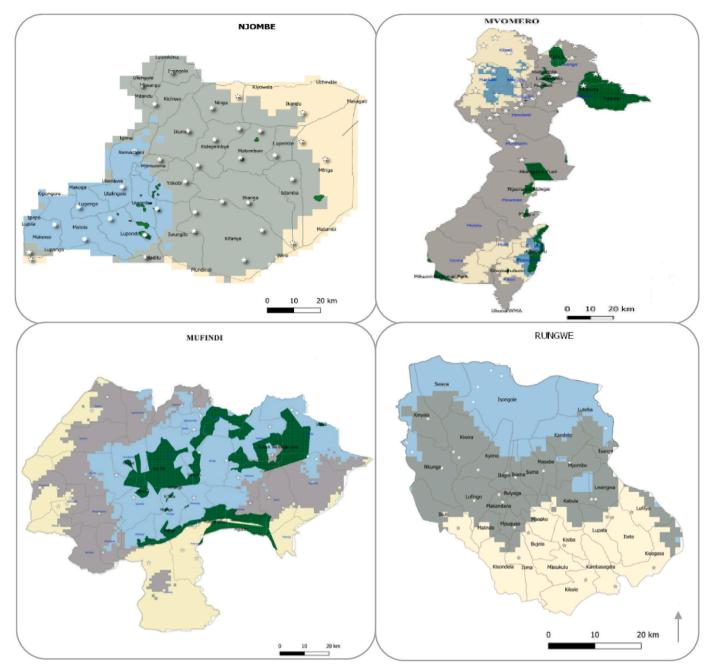


Fig. 2. Agro-ecological clusters across the four study sites. Note: Blue colour denotes the high cluster grey the mid cluster and cream the low cluster while green denotes the forested land and the white stars denotes the sampled villages.

(Table 3). The variables included demographic variables (Alvarez et al., 2018) and variables that capture livelihood activities and household asset endowments (Dorward et al., 2009; Tittonell, 2014). The four asset variables include the asset index (constructed following the Filmer and Pritchett, 2001 methodology), Tropical Livestock Unit (TLU) (following Njuki et al. (2011)), total land owned by the household and group membership as a proxy for social capital. Livelihood activities were calculated as a dummy variable from households representing whether a household was engaged in that activity or not (Schoneveld et al., 2019).

Clusters were compared not only using the variables included in the multivariate analysis but also using variables that condition uptake of LED practices. This includes household income, access to markets, and average milk price, which represent investment capacity and market articulation (Michalscheck et al., 2018; Tittonell et al., 2010).

3.4.2. LED practices at the household level

Indicators for households' LED practices were mainly guided by their contribution to productivity (intensification) and emission intensities, as discussed by Ericksen and Crane (2018). The technical practices were grouped into the following three categories:

(i) *Improved feed quality and quantity*, such as fodder production and feeding concentrates, were used to denote the provision of sufficient high-quality and high-protein feed to cows (Thornton and Herrero, 2010). Further, fulltime water access and feed conservation were used as proxies for management of dry season water and feed availability constraints. A study by FAO (2019) conducted in Tanzania demonstrated that improved feeding practices can emission intensities by 8–35%. Additionally, zero-grazing i.e. confining animals to limited physical space in which they are fed, and milked was used as a proxy for

Table 3

Variables used to cluster producers.

Agricultural System	100 (202 ⁻	1) 102072

Description

Mean

Table 4

Low-emission practices at the household level. Variable

Variable Mean Des (SD)		Description	Proxy for	
Education	3.05	Highest education of Household	Demographic	
	(1.04)	head		
		Ordinal with 6 levels ($0 = No$		
		formal education, $1 = primary$		
		1–3, 2 = primary 4–7, 3 =		
		secondary $1-4, 4 = A$ -levels form		
		5-6, $5 = college$, $6 = University$)		
Age [years]	51.03	Age of the household head	Demographic	
	(12.04)	[years]		
Gender [%	88.77	Gender of the household head [1	Demographic	
male]	(31.58)	= male 0 $=$ female]		
Household size	5.83	Household members 16-65	Demographic	
[number]	(2.31)	years [No]		
Ethnicity [%	78.31	Dummy for ethnicity $[1 = yes, 0]$	Demographic	
indigenous]	(41.22)	= no]		
Land [acres]	10.65	Total land holding [acres]	Asset	
	(14.28)		endowment	
TLU [index]	9.51	TLU score [score]	Asset	
	(15.99)		endowment	
Asset [index]	0.53	Asset index [score]	Asset	
	(0.15)		endowment	
Group	42.26	Dummy for group membership	Livelihood	
membership [%]	(49.41)	[1 = yes, 0 = no]	activities	
Dairy sales [%]	68.19	Dummy income dairy $[1 = yes,$	Livelihood	
	(46.59)	0 = no]	activities	
Food crop [%]	71.17	Dummy food crops revenue [1 =	Livelihood	
	(45.31)	yes, $0 = no$]	activities	
Livestock sales	77.22	Dummy livestock revenue [1 =	Livelihood	
[%]	(41.96)	yes, $0 = no$]	activities	
Casual	10.20	Dummy casual income $[1 = yes,$	Livelihood	
employment [%]	(30.28)	0 = no]	activities	
Business [%]	58.12	Dummy off farm business [1 =	Livelihood	
	(19.23)	yes, $0 = no$]	activities	
Formal income	11.13	Dummy off farm formal $[1 = yes,$	Livelihood	
[%]	(31.47)	0 = no]	activities	
Forest	37.50	Dummy for forest plantations	Livelihood	
plantation [%]	(48.43)	income $[1 = yes, 0 = no]$	activities	
Cash crop	68.02	Dummy for cash crop revenue	Livelihood	
revenue [%]	(46.65)	[1 = yes, 0 = no]	activities	
Other income	22.27	Dummy for non-labour income	Livelihood	
[%]	(41.62	[remittances, dividends, and pension]	activities	

improved efficiency in animal feeding and husbandry (Aguirre-Villegas et al., 2017).

(ii) improved animal health and husbandry practices, - We use deworming, spraying, use of artificial insemination, and improved bulls for insemination and calving interval, as proxies for animal health and good husbandry practices. Improved animal health through deworming and tick management (spraying/dipping) can significantly improve productivity and reduce emission intensities by reducing mortality and morbidity and enabling animals to invest energy in milk production. Having an appropriate calving interval between 12 and 14 months and proper breeding strategies helps in maintaining productivity and can reduce emission intensities by 20-35% (FAO, 2019).

(iii) Proper manure storage and management can reduce emissions from manure by up to 90% by reducing anaerobic decomposition (Ericksen and Crane, 2018). Time taken before incorporating manure into soils and the use of biodigesters were used as proxies for optimal manure management. Appropriate use of manure on soils can contribute to more efficient nutrient use, soil quality, and crop productivity while replacing synthetic fertilizers and their associated emissions (Chadwick et al., 2011). Use of biodigesters that capture methane and convert this into energy also significantly reduce emissions associated with manure, while also contributing to household energy needs and replacing non-

	Variable	Mean (SD)	Description
Feeding	Feed conservation [%]	11.05 (31.37)	Dummy variable for practising feed conservation
	Fulltime water access [%]	18.28 (38.66)	Dummy variable for cows having fulltime water access
	Grow fodder [%]	42.68 (49.48)	Dummy variable for whether household grow improved fodder
	Feed concentrates [%]	71.76 (45.03)	Dummy variable for households that feed cattle concentrates
	Zero grazing [%]	54.33 (49.83)	Dummy variable for households that practice zero-grazing
Animal health and	Crossbred cows [% improved]	62.33 (47.03)	Proportion of cows that are Crossbred cows
husbandry	Deworm within every three months [%]	41.41 (49.27)	Dummy variable for deworming cattle at least once every three months
	Spray fortnightly [%]	61.39 (48.70)	Dummy variable for spraying/dipping cattle every fortnight
	Inseminate using improved bull [%]	60.28 (48.95)	Dummy variable for households using improved bulls for insemination
	Inseminate using AI [%]	3.91 (19.39)	Dummy variable for households using AI for insemination
	Calving interval below 14 months [%]	53.99 (49.86)	Dummy variable for households with a calving interval below 14 months
Manure management	Use manure on the farm within three months [%]	15.98 (36.66)	Dummy variable for the use of manure on the farm within three months
	Biodigester [%]	2.12 (14.43)	Dummy variable for households with a functional bio-digester

renewable alternatives (Chadwick et al., 2011; Herrero et al., 2016).

Table 4 describes the above LED variables. To facilitate comparison and interpretation, we mainly use dummy variables. This data on LED practices were subsequently used to compare the degree of adoption across the clusters. Further, a composite index was developed using factor analysis. This was used to compare the adoption of LED across various marketing options and farmer types.

3.4.3. Validation and barriers to uptake of LED practices

The cluster analysis results were validated with a subset of research participants and relevant experts through multi-stakeholder workshops, conducted in February 2019. Expert participants included a mix of representatives from government, local development organiations, farmer organizations, and dairy-relevant enterprises. In these workshops, the household typologies were presented and participants reflected on how well they reflected their realities. The validation workshops were also used to identify the different barriers to uptake of practices that should be accounted for LED intervention design. Participants were asked to reflect on adoption barriers particular to each cluster and how farmers in each cluster are likely to respond to different incentive mechanisms. This enabled us to differentiate between structural and cluster-specific barriers to uptake of LED practices. A total of 110 representatives from Njombe and Rungwe districts were involved in these workshops. Although similar workshops were not held in Mufindi and Myomero due to budgetary constraints, stakeholders from these districts participated in a national workshop where their views were incorporated.

4. Results

4.1. Farmer typologies

The first stage of analysis produced six distinctive clusters of farmers through cluster analysis. The largest cluster contained 281 households (cluster 4), representing 24% of the total sample population, and the smallest cluster of 109 households (cluster 6), representing 9% of the sampled population. The demographic characteristics of each cluster are summarized in Table 5 and Fig. 3. This data shows that cluster membership is strongly influenced by wealth indicators, whether farmers are engaged in business activities, whether they are part of a farmer's organization, and whether income is derived from dairy production.

Based on these descriptive statistics and workshop results, we characterize each cluster as forth:

4.1.1. Cluster 1: subsistence farmers

This cluster of farmers has the highest proportion of respondents with no formal education (15.72%). They also have the lowest asset index (0.45) and the lowest household annual income (Fig. 3). Respondents in this cluster do not engage in milk sales and any off-farm business activities. Almost two-thirds of income is obtained through cultivation activities (e.g., cash crops, food crops, and/ timber) (Fig. 4). This cluster, however, has the highest TLU (13.29), but only half of the cluster (49%) depend on livestock sales despite owning significant livestock. This cluster is, therefore, comparatively poor and vulnerable, with livestock mostly meeting the consumptive needs of the households, functioning foremost as a safety net.

4.1.2. Cluster 2: diversified farmers

This cluster of farmers is comparatively diversified. Farmers in this cluster have multiple sources of income, with all farmers deriving an income from both dairy and off-farm business activities. While most households are engaged in a variety of crop production activities (61%), dairy (100%) and business (100%) are the primary sources of income. The cluster is comparatively affluent, scoring highly on the asset index (0.59), having some of the highest annual incomes, and owning significant TLU and land. None of the farmers in this cluster is engaged in farmer groups, suggesting prioritization of off-farm economic activities.

4.1.3. Cluster 3: livestock-dependent farmers

We consider this cluster as being livestock-dependent, due to their heavy reliance on income from dairy and other livestock activities and high TLU ownership. With regards to livelihood portfolios, respondents in this cluster depend mainly on livestock for their income. All the respondents (100%) derive an income from dairy, followed by income

Table 5

Demographic characteristics of farmer groups.

from livestock sales (83%). Approximately 59% of household income originates from dairy and livestock sales (Fig. 4). The cluster is average in asset ownership. This is the only cluster where income from dairy comprises most of the household income. None of the respondents in this cluster have an off-farm business income.

4.1.4. Cluster 4: farm specialists

This cluster is characterized by high on-farm diversification, with significant dependency on farm-based activities (84% of income). Farmers in this cluster generally cultivate the largest number of different cash and food crops, and timber, though dairy is the backbone of their livelihoods. On average, farmers in this cluster own large areas of land (12.9 acres), only exceeded by Cluster 5. The importance of agriculture is reflected by all farmers being engaged in farmer groups.

4.1.5. Cluster 5: wealthy

Farmers in this cluster are the wealthiest. They rank highest on the asset index (0.60) and have the largest average land size (14.2 acres). Additionally, they have access to multiple sources of income, both on-farm and off-farm, with all (100%) the respondents in this cluster having an off-farm business income. They also derive an income from cash crops (58%) and/or food crop sales (76%). Livelihood composition in this cluster is similar to Cluster 2, though business activities are of lesser importance than on-farm activities. This is reflected in widespread participation in farmer organizations.

4.1.6. Cluster 6: marginalized entrepreneurs

Respondents in this cluster can be characterized as non-dairy, offfarm entrepreneurs because none of the respondents derives income from dairy, while all derive income from off-farm, notably business, activities. Farmers in this cluster also tend to earn a lower income, possess less land (7.95 acres), and be less asset endowed than farmers in most other clusters, except subsistence farmers, though they do own significant TLU (11.34). Off-farm activities take priority over dairy for members of this cluster.

4.2. Geographic distribution of the farmer clusters

The clusters are distributed fairly evenly across the districts. In Njombe, however, farm specialist and wealthy farmers are comparatively prevalent (Fig. 5). This can be attributed to the district's high level of collective organization and mature dairy market. Rungwe district has a more balanced representation across the six clusters than Njombe, despite also having a comparatively dynamic dairy sector. The larger number of subsistence farmers and livestock dependent farmers in Rungwe is foremost a product of land pressures in its more productive

Variables	1	2	3	4	5	6	Chi/F-Statistic
Total cluster size (n)	229	132	258	281	167	109	
Demographics							
Education ordinal	2.72	3.21	2.95	3.11	3.11	2.90	35.0***
Gender of HHH [% male]	90.39	91.66	90.00	83.15	90.41	90.82	11.49
Age HHH [Years]	51.79	50.14	50.75	52.25	50.71	48.56	11.2
Total land [Acres]	8.70	10.86	8.65	12.92	14.19	7.95	58.4***
Wealth index [Score]	0.45	0.59	0.52	0.57	0.60	0.49	30.4***
TLU [Score]	13.29	9.33	11.56	5.67	6.61	11.34	62.5***
Household size [number of members]	5.99	6.02	5.88	5.46	5.70	6.29	2.80
Origin of household head [% indigenous]	83.84	74.24	70.38	82.43	74.25	86.23	21.4***
Dummy casual income [% yes]	7.86	0.45	9.23	15.05	10.17	11.92	13.46
Dummy formal income [% yes]	6.55	15.91	12.69	14.33	9.58	5.50	15.24**
Dummy non labour-off-farm income [% yes]	16.15	20.45	19.23	28.13	28.14	20.18	3.24
Dummy revenue livestock [%]	49.34	82.57	83.07	91.76	92.22	55.04	193.9***

*** Significant at 1% level of significance.

** Significant at 5% level of significance

* Significant at 10% level of significance.

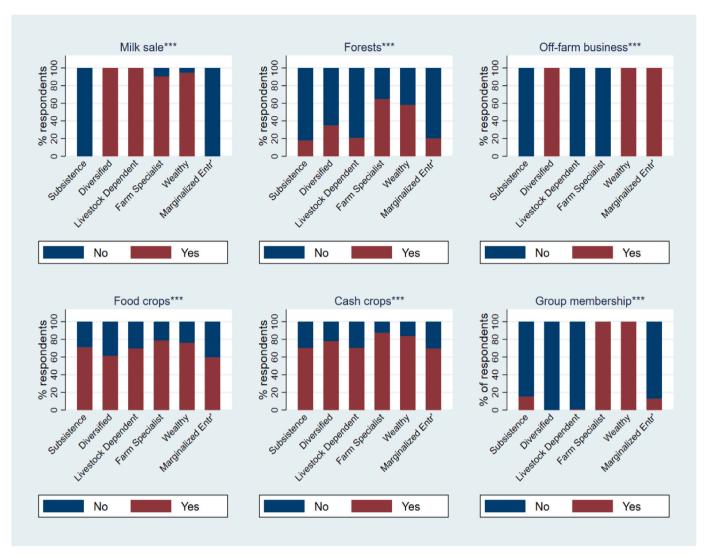


Fig. 3. livelihood activities across the six clusters.

Note: Marginalized Entr represents Marginalized Entrepreneurs.

*** significant at 1%, ** significant at 5%, * significant at 10% level of significance.

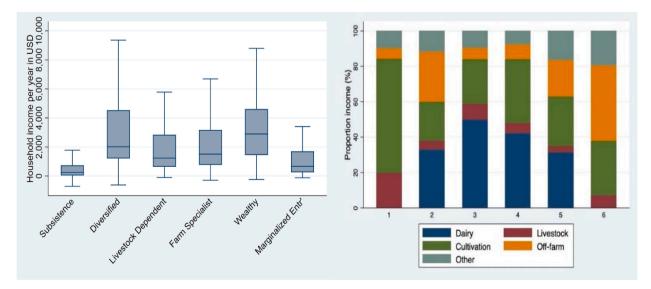


Fig. 4. Total household income by cluster.

X-axis represents the clusters; 1 = Subsistence Farmers, 2 = Diversified Farmers, 3 = Livestock Dependent, 4 = Farm Specialist, 5 = Wealthy Farmers, and 6 = Marginalized Entrepreneurs. Note: Other income includes remittances, pensions, and dividends; Off-farm includes business activities and employment; Cultivation cash crops, food crops and timber. 1USD = 2300TZS as at the time of the survey in 2018.

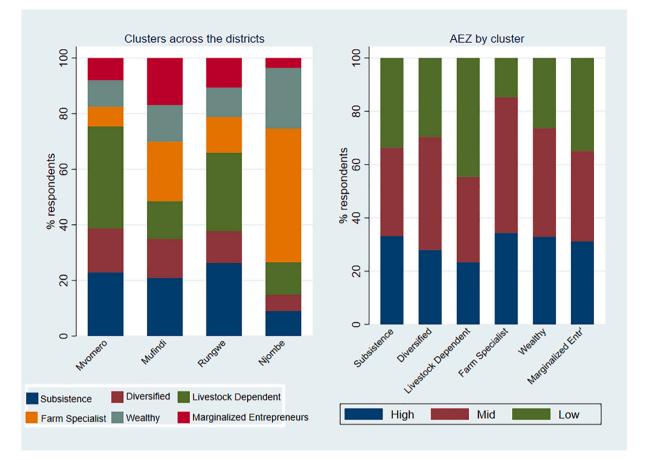


Fig. 5. Farmers typologies across the four districts.

Note: High represents a dummy variable for all the high Agro-ecological clusters across the districts (Fig. 2), Mid represents all the mid Agro-ecological clusters while low represents all the low cluster in the four districts.

highland areas. This constrains household capacity to diversify into cash cropping. In contrast, the peripheral lowlands of Rungwe are dominated by more extensive dairy systems, though lack of (public) intervention in the collective organizations and large distances from major towns and tarmacked roads inhibit commercialization.

Marginalized entrepreneurs are comparatively prevalent in Mufindi. This reflects Mufindi's dynamic and diversified rural economy. Diverse livelihood options are available to farmers because of the prevalence of major corporations, proximity to a major national highway, and relative abundance of land. Because many farmers are not reliant on dairy income, dairy markets remain poorly developed and largely informal. As expected, subsistence farmers and livestock dependent households are comparatively prevalent in Mvomero. Some of its more arid areas are dominated by pastoral Maasai communities who keep cattle in more extensive systems. In higher elevation areas of Mvomero that are more amenable to zero grazing systems, more diversified and/or dairyoriented farmers could be observed. Based on the biophysical clusters described in Fig. 2, subsistence farmers and marginalized entrepreneurs tend to be located in low altitude areas, while wealthy and farm specialist households are especially prevalent in high altitude areas. (Fig. 5). This illustrates that even within districts, agroecological factors strongly influence socio-economic composition.

4.3. LED practices across clusters

This second stage of analysis examined the adoption of LED practices by cluster. Fig. 6 shows that the uptake of LED practices varies significantly across the clusters. Wealthy and farm specialist households are most likely to employ LED practices, followed by livestock-dependent and diversified households engaged in dairy marketing (e.g., subsistence farmers and marginalized entrepreneurs). This highlights that dairy marketing and adoption of LED practices are intimately interrelated.

Furthermore, results show that as farmers intensify, there is a clear preference for zero-grazing, keeping improved cows, animal health, and better feeding practices (e.g. by growing improved fodder and feeding concentrates). Manure and feed management are not prioritized by any of the clusters, and neither is the use of AI, with most farmers instead opting for improved bulls. This is unsurprising because manure management does not directly affect dairy output and AI can be expensive, difficult to access, and subject to quality issues. Subsistence farmers and marginalized entrepreneurs appear to prioritize spraying and reproductive practices, with maximization of herd size prioritized over dairy output. Across all the groups, practices are adopted in a similar pattern across all the clusters, primarily differing in the extent of adoption. This indicates that LED practices are typically adopted in a specific sequence, reflecting common preferences and/or constraints.

4.4. LED practices across the districts

Major differences in the prevalence of practices can also be observed between districts, suggesting that geographic factors also influence adoption (Fig. 7). Farmers in Njombe are more likely to have adopted a wider array of practices, including also those pertaining to animal health and feed management. This is attributed to long term training on feed management by development organizations and the local district extension service. For other practices, farmers in Rungwe largely performed on par with those in Njombe. One notable exception is manure

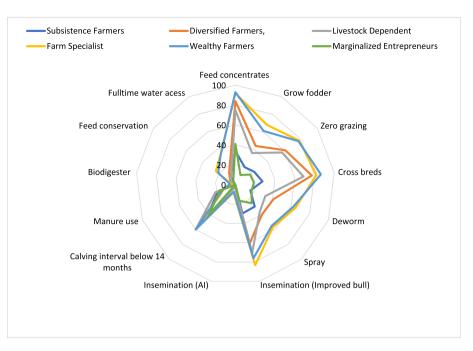


Fig. 6. Practices across the clusters.

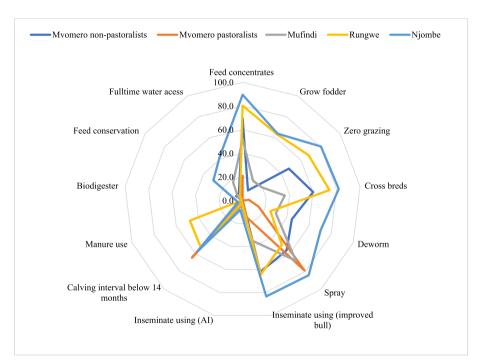


Fig. 7. LED Practices across the districts.

management.

This can be attributed to comparatively small farm size and population pressures in its highland areas, with manure often used to fertilize cash crops especially bananas. Rungwe also has multiple short rainy seasons, meaning farmers can apply manure on their farm more frequently compared to the other districts where rainy seasons last as long as six months. In Mufindi and Mvomero, animal health and reproduction are prioritized, reflecting the relative importance of other livestock activities over dairy due to the absence of more mature dairy markets. Less fodder cultivation in those districts also reflects the greater availability of grazing land. These findings suggest that structural constraints and conditions further mediate what practices farmers adopt. In all the districts, full-time access to water, the use of AI, feed conservation and having a biodigester scored low.

4.5. Barriers to uptake of LED practices

This section presents the third stage of results on barriers to uptake of LED practices, based on survey data and validation workshops. Three major barriers to uptake of LED were identified: 1) marketing and collective action related barriers, 2) availability of inputs, and 3) diversified livelihood objectives.

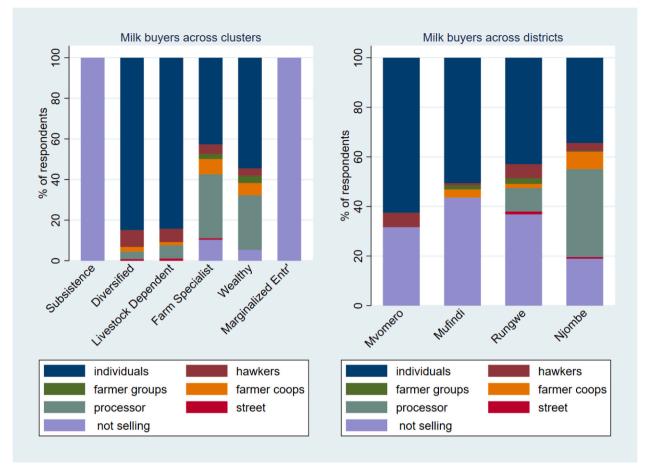


Fig. 8. Milk buyers across clusters.

Marginalized Entr represents Marginalized Entrepreneurs.

4.5.1. Marketing and collective action related barriers

Households that do not sell milk did not adopt most LED practices because they have little incentive to adopt LED practices. Farmers contend that the milk market is highly volatile, with milk prices reducing during the wet season due to supply gluts. There are no standards or set guidelines within the market that explicitly incentivize the adoption of LED practices. Most farmers, irrespective of cluster, sell milk to individual buyers rather than to processors. There are no processors in Mufindi and Mvomero that source milk directly from farmers (Fig. 8). The farm specialists cluster has the highest percentage of respondents who sell milk to processors (31%), followed by the wealthy cluster (27%), as shown in Fig. 8. None of the buyers is demanding uptake of LED as a pre-condition to buy milk from producers. However, producers who sell to particularly processors can access personalized extension support provided by processors for free to help raise productivity, though they do need to pay for inputs.

As such, formal marketing (e.g. through processors and

cooperatives) is systematically associated with higher overall LED performance than farmers marketing through informal channels (Table 6). Nevertheless, differences in performance between marketing channels do suggest that some of the LED performance is attributable to formal buyers, an interpretation supported by workshop participants. According to farmers, while it is rarely a major source of inputs, extension support provided by processors, and cooperatives, strengthens farmer confidence and capacity to intensify. This facilitates the adoption of certain practices, especially those that directly enhance milk yields. Manure management, however, is rarely promoted by processor or cooperative extension service agents.

In Mvomero and Mufindi, between 88 and 92% of farmers sell their milk to individuals due to the absence of processors and well developed cooperatives in Mufindi, while in Mvomero most processors scource milk from intermediate traders who aggregate milk from producers. LED performance for those farmers ranges from 0.32 (livestock dependent farmers) to 0.48 (wealthy farmers), while farmers in the two clusters

Table 6

Cluster	Not selling	Individuals	Hawkers	Cooperative	Processor	Average
Subsistence farmers	0.32					0.32
Diversified farmers		0.55				0.56
Livestock dependent		0.52			0.60	0.53
Farm specialists	0.53	0.57	0.62	0.65	0.69	0.63
Wealthy farmers		0.56		0.61	0.73	0.63
Marginalized entrepreneurs	0.33					0.33
Average	0.35	0.54	0.60	0.64	0.69	0.53

Note: the values represent a composite index score with 0 denoting lowest adoption of LED practices and 1 highest level of adoption. Cells with n < 10 are left empty.

that do not sell at all on an average score between 0.17 and 0.18. Like in Rungwe and Njombe, those that do not sell any milk typically underperform, as would be expected, suggesting that dairy commercialization both enables and incentivizes intensification. While the non-adoption of better practices reduces the household capacity to produce a marketable surplus, the absence of marketable surplus also reduces the ability to adopt better practices. This represents a vicious circle that interventions should aim to disrupt through interventions that combine on-farm technical support with support of market institutions such as linking technical extension services with a working marketing model as demonstrated by private processors in Rungwe.

Poor governance of farmer organizations was also cited as a major adoption barrier. Processors pay farmers through farmer organizations rather than directly. Consequently, when group leaders are inefficient or mismanage funds, farmers encounter payment delays. This undermines farmer capacity to plan and discourages investment in better practices. Other market-related challenges include high transportation costs and high operational costs of cooling centres.

4.5.2. Availability of inputs

Access to and efficient delivery of AI services was noted as problematic across all the clusters. This was evident from both the survey and workshop results. Farmers prefer to use improved bulls instead of AI, because of the challenges and uncertainties associated with AI, such as poorly trained and experienced AI providers, poor quality of semen, lowsuccess rates, high costs, lack of proper storage and transporting equipment, and large distances. This was observed across all the farmer clusters and across all the districts. Although improved bulls are widely available, there are fears of eroding the genetic potential of the bulls and the dairy herd in general because of inbreeding and declining genetic quality. This was often mentioned in Rungwe and Njombe in particular, where respondents noted that the productivity of their cattle breeds is deteriorating instead of improving.

Insufficient availability of pre-mixed feed concentrates is a challenge across all the sites. Farmers primarily use millers' byproducts, such as maize germ and sunflower seed cake, so they are not able to ascertain the types and amounts of nutrients provided to their animals. However, wealthy and farm specialist clusters often received training on how to mix their rations through their farmer groups. Districts like Rungwe, where cereals are not produced on a large scale, experience higher prices for the byproducts because they must be transported from other regions. This also applies to households located far from major roads and marketing centres. High feed costs are widely cited as a leading barrier to intensification.

4.5.3. Pluri-active livelihoods (diversified livelihood priorities)

Farmers in the two clusters not selling milk were often unmotivated to intensify. For example, within pastoral communities, herd management is not oriented toward commercial dairy optimization. Instead, cows produce milk for household consumption, and cattle are however mainly a measure of wealth. Acknowledging that cattle have multiple and variable functions in household livelihoods is important in understanding producers' priorities and motivations (Weiler et al., 2014). This is particularly true in locations such as Mvomero districts, which have larger herds of local cattle managed under pastoral logics.

The subsistence farmers and marginalized entrepreneurs keep more indigenous cows. They have incentives to invest in local breeds that are managed for draft power, manure, and storage of wealth. For instance, in Mvomero, indigenous breeds are much better adapted than improved breeds to the region's harsher environments, which is characterized by poor feed quality, high temperatures, and heavier disease loads. Therefore, while local breeds produce lower amounts of milk, they make substantial contributions to livelihoods in other ways, especially ones that prioritize environmental adaptiveness. The low adoption of LED dairy practices in these clusters thus appears to be associated with a different set of livelihood priorities relating to livestock keeping.

5. Discussion

5.1. LED adoption pathways

The overarching objective of this article is to support the development of LED strategies that account for heterogeneity in farmers' capacities, priorities and interests. Our analysis reveals six distinct farmer types with various degrees of uptake. Wealth, low TLUs, and diversification of income sources were found to be a defining characteristic for the wealthy and the farm specialist clusters, which also are most likely to adopt LED practices. The wealthy farmers resemble the "stepping up" category of Dorward et al. (2009). Farmers with capital and other resources at their disposal to invest in LED practices are the most obvious candidates for LED interventions involving capital intensive practices. The farm specialists cluster does not perfectly fit any of Dorward et al.'s (2009) categorizations but does resemble the "moving in" farmers of Schoneveld et al. (2019) because they are investing non-farm income into their farms. Many of these farmers were not previously cattle keeping households, but, through external assistance, have received improved cattle and training on dairy production. Households in Njombe had received more support compared to other districts. This shows that long-term external investment, both in assets and knowledge, have been key drivers of adoption for LED practices (Liu et al., 2018). Because farmers in these two clusters are already familiar with many LED practices, upgrading is not likely to require significant technological support (Schoneveld et al., 2019). Instead, such farmers need to be sufficiently incentivized to adopt a larger variety of LED practices, including those that do not directly translate into productivity gains. This could be achieved through increased sensitization and extension. Because farmers in these clusters are heavily reliant on functional market demands and conditions, strategies that enhance market efficiencies, such as proper governance of farmer organizations, market standards, access to cooling centres, and access to better quality inputs, could incentivize further investment in LED. Emission reduction potential, however, is lower for this cluster. Nevertheless, emission intensities could be further reduced by enabling genetic improvements by strengthening the quality and efficiency of AI services, improving the quality of supplementary feeds (FAO, 2019; Herrero et al., 2016), and making manure management technologies more accessible. However, a critical review of farmers' benefits within such systems needs to be periodically assessed because increased productivity can reduce milk prices due to increased supply, thus offsetting benefits to producers (Chavas and Nauges, 2020). This highlights that improving productivity should not be conflated with improving profitability, an important fact often overlooked in technocentric approaches to promoting LED.

Diversifying and livestock-dependent households were found to be moderately intensifying. These clusters are also moderately asset endowed, though with more TLUs and a greater mix of improved and local cows compared to the wealthy farmers and farm specialists. Diversified farmers do not fit neatly into the categories of Dorward et al. (2009). However, they do resemble the "moving through" households of Schoneveld et al. (2019) because of their moderate and sometimes transient commitment to dairy. They are not members of farmer groups and often view livestock as an asset that can be transacted rather than as a productive resource. Interventions that would encourage such households to realize yield gains without diverting labour from other activities could incentivize the adoption of LED practices and reduce the motivation to maintain large herds. Because these producers are comparatively time-constrained, labour saving technologies such as chaff cutters deserve to be more actively promoted, as well as those that complement other farming activities (e.g. manure management). This could be augmented with value chain development and understanding of producer's production aspirations (Verkaart et al., 2018). When milk markets are not functional or too volatile, these households tend to prioritize income-generating activity that are more stable and involve fewer transaction costs. With the right mix of interventions, these

farmers could contribute to significant reduction in GHG emission intensities in the short and medium term.

Subsistence farmers and marginalized entrepreneurs experience the lowest adoption rates of LED practices. They are generally poorly linked to markets, receive few extension services, and have little experience keeping improved cattle. The subsistence farmers resemble the "hanging in" categorization by Dorward et al. (2009) since they are characterized by low resource endowment and vulnerability. Because these households are resource-constrained and do not sell milk, they tend not to invest in dairy intensification and receive few extension services. Interventions that address both the knowledge and resource gaps for such farmers would therefore be most appropriate. This cluster would, however, require more long-term intervention as has been done in Njombe, involving both sustained organizational and technical training. It is also possible that these farmers might drop out of dairy farming altogether in the absence of adequate marketable surplus and reliable market access.

Interestingly, the "marginalized entrepreneurs" cluster – mostly found in Mvomero (semi-arid) and Mufindi - ranked the lowest in terms of uptake of all the LED practices, despite benefitting from alternative sources of income that could be invested into their dairy cattle. This cluster most closely resembles Dorward et al.'s (2009) "dropping out" category, meaning that they are clearly not motivated to practice dairy commercially and thereby will likely be less responsive to productivityenhancing technologies. Moving these farmers to intensive dairy production might be difficult. Dairy nevertheless plays a critical role in household nutritional security. Provision of livestock health services such as control of tick-borne disease, extension services, and other feedrelated services (FAO, 2019), such as sustainable management and protection of grazing lands - are more in line with their livelihood priorities and will ensure increased and consistent milk supply. To reduce GHG emission intensities, innovative synergies between farming households and pastoralists could be explored, such as having farmers provide crop residues as feed for pastoral herds in exchange for depositing manure on farmers' fields. In Mvomero, pastoralists are slowly beginning to purchase or lease land for food and fodder production. This gives them an alternative source of income during the dry season, but also gives them or part of their families a reason to stay in the same place. This cluster is, therefore, not a prime target for the adoption of dairy-specific LED practices. Structural and institutional issues, such as land tenure reforms and social safeguarding, would have to be resolved before LED investments are likely to be viable.

5.2. Linking low-emission development to agricultural transformation trajectories

The pathways approach acknowledges multiple trajectories in achieving transformation (Leach et al., 2010), illuminating the nonlinear, interconnected, and complex interactions shaping outcomes (Scoones et al., 2020; Tomich et al., 2019). For instance, adoption of certain practices differs more between geographies than between cluster due to distinctive differences in local histories, climatic conditions, institutions, market maturity, and input and service availability and accessibility. Notably, as the case of Njombe illustrates, a unique culture of collective action and strategic collaboration between development organizations and the government has played a critical role in intensifying production, promoting collaborative action, and catalyzing dairy sector investment. This illustrates how future investments in the uptake of LED practices would demand both direct investment in support of farmers' uptake of LED practices and investment in coordination (Giovanni et al., 2018) and alignment of multiple stakeholders' activities along the value chains and in the development space.

Agroecological constraints also shape how adoption at scale can be realized. Extensive production systems involving local cattle are often more common in semi-arid conditions (Nell et al., 2014) Even though high-altitude areas tend to demand more intensive systems, households in peripheral areas where inputs and services are less accessible and land constraints less acute are often required to adopt less intensive production systems. Despite agroecological differences within and across study districts, public interventions rarely account for geographic variabilities within their administrative jurisdiction or discriminate against lesser intensive production zones. In Tanzania's highlands, peripheral areas within a district, are rarely considered in local government planning or are expected to transition to more intensive production systems that many cannot sustain. Dryland pastoral and agropastoral systems are too rarely prioritized because these poorly align with sectoral commercialization and LED objectives (Katjiuongua and Nelgen, 2014; Nell et al., 2014). Even though this study only captured a small segment of farmers producing dairy within such systems, they are vitally important because such farmers account for 70% of national milk output (Michael et al., 2018). Raising the productivity of such farmers while maintaining their production systems can serve national food and nutritional security objectives, yet they are widely sidelined in intensification and LED discussions.

This leads us to question the operationalization of LED as a clearly defined on-farm technological package. LED is often not positioned in the food system transformation discourse. Doing so in the future could help better account for interdependencies across production systems, ecological and cultural (Weiler et al., 2014) diversity as well as farmers' production strategies (Verkaart et al., 2018). Our results suggest that research and interventions should focus more deliberately on cocreating intervention options that respond to the needs and priorities of local communities (Leach et al., 2010) rather than focusing exclusively on technology transfers (Geels, 2002). This is especially pertinent to dryland pastoral systems that are especially vulnerable to environmental degradation and climatic shocks yet can still (moderately) intensify and become more resilient if external support is better aligned with local priorities and conditions. Our own focus on (semi-)intensive dairy systems in highland environments - due to their emission reduction potential - was admittedly insufficiently calibrated to fairly analyze lowland systems. We, therefore, recommend that future research adopt more holistic food system approaches (Tomich et al., 2019) when examining LED implementation pathways. To help better embed lesser intensive/intensifiable production systems in the rapidly evolving LED discourse, this ideally would involve bottom-up approaches that account for the socio-ecological conditions, livelihood strategies, and cultural norms that have long inhibited systems innovation (Hebinck et al., 2018). Failing to adequately account for such systems in future LED strategies could deprive especially marginalized and vulnerable communities of new climate finance opportunities.

6. Conclusion

This article analyzes the heterogeneity of smallholder dairy production systems in Tanzania in relation to LED. In doing so, we advance the literature on smallholder heterogeneity/ actor-disaggregated policymaking (Alvarez et al., 2018; Dorward et al., 2009; Tittonell et al., 2015; Schoneveld et al., 2019), as well as the literature on locally-adaptive LED (Ericksen and Crane, 2018; Herrero et al., 2016). We demonstrate the importance of designing interventions that account for both farmer socio-economic heterogeneity and structural barriers to uptake. Departing from mainstream farming systems typology approaches, this study highlights how, going forward, differentiated farmer capabilities and strategies deserve to be more explicitly accounted for when articulating sustainable and inclusive pathways. In particular, we show that wealth, off-farm income sources, cattle breeds, and degree of income diversification are important sources of heterogeneity within Tanzanian dairy systems and, by extension, determinants of intensification. We furthermore demonstrate that the adoption of LED practices is simultaneously shaped by geographic, agroclimatic conditions and market conditions, and (donor) support legacies. These results illustrate that "one-size-fits-all" LED strategies are likely to result in sub-optimal outcomes; not only concerning emission reduction but also socio-economic development. Ultimately, successful LED is contingent on donor and state ability to nest LED strategies within local development trajectories and priorities, as well as emergent sustainable food systems targets. The ways these different objectives and priorities articulate with each other is fundamental to understanding who LED is intended to serve.

This article points to the need to consider multiple transformation trajectories in achieving LED. First, variants of technological packages plus market-based interventions will appeal to better-resourced farmers that are more intensified and dependent on dairy incomes. While this cluster represents a potential for 'quick wins', GHG reductions from targeting this cluster are likely to be modest. Because these farmers also tend to be more affluent, technologist and market-oriented LED interventions are also poorly consistent with inclusive development goals. Second, more moderately intensified households often experience more pronounced barriers to adoption, but with the right support, these are surmountable. Explicitly targeting such farmers will deliver greater benefits with respect to GHG reductions and inclusive development. A mix of both market incentives, value chain development, and concessionary access to better quality inputs and extension services could serve to catalyze adoption of LED practices. Finally, a conceptualization of pathways that are grounded within a food system approach rather than as a technological package would be required for households that keep more indigenous breeds and are currently not adopting many LED practices. Using a bottom-up approach that accounts for the real needs of pastoral dairy farmers would lead to more inclusive rural development, as well as enhance resilience to climate change and reduce land degradation.

The findings challenge the notion that LED is a question of a simple technological fix. We show instead that intensification, as currently conceptualized, is not equally accessible or appealing to everyone. We believe that moving beyond the technocentric approach to a food-systems approach will help LED become more synonymous with inclusive rural development. A "one-size-fits-all" promotion of LED practices would neglect a large segment of potential beneficiaries and risk falling flat, or worse, accentuate existing inequalities. An actor disaggregated intervention approach, where initiatives are tailored to fit the interests and goals of distinct kinds of farmers, has a greater chance of simultaneously achieving GHG emission reduction targets and inclusive socio-economic development.

Declaration of Competing Interest

None.

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