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Analyzing dominance of dairy climate smart agricultural practices and implications on milk yield: Evidence from Kenya

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Abstract

The study aimed at identifying and clustering farmers into typologies of dominant dairy CSA practices and assessed their linkage to milk production. Latent Class Analysis (LCA) was applied in identifying typologies from a sample size of 665 dairy farmers in selected counties in Kenya. Five typologies; health management dominated typology (Typology 1), health and animal husbandry dominated typology (Typology 2), health, animal husbandry, manure and improved feed dominated typology (Typology 3), health, animal husbandry, improved feed and fodder dominated typology (Typology 4), and health, animal husbandry, improved feed and fodder and fodder conservation dominated typology (Typology 5), were identified. The results showed low dominance of over half of the practices studied. Besides, there was low uptake of dairy CSA practices since majority of the dairy farmers belonged to Typologies 1 and 2, which had the lowest number of dominant practices. There were significant differences in milk yield across typologies. Typology 5, with the highest number of dominant practices, had the highest milk average, while Typology 1 with the least number of dominant practices had the lowest milk yield. Higher milk yield was attributed to composting, hay and silage making. The study recommends intensified promotion of dairy CSA practices with attention to fodder conservation-related practices so as to exploit co-benefits of improved milk yield.

Keywords: Latent class analysis, dominance, dairy, climate smart agriculture practices, typologies, milk yield

1. Introduction

Climate change effects such as rising temperatures, increased frequency and severity of droughts and floods, and changes in precipitation patterns (Aryal et al., 2018; Swinnen et al., 2022; Jones et al., 2023), pose threats to the global food systems (Jones et al., 2023; Swinnen et al., 2022). In 2018, agriculture absorbed a quarter of climate change global economic impacts, of which absorption by livestock ranked second after crops (Escarcha et al., 2018). The effects are projected to increase rapidly and at a broader scale, with far reaching effects in developing countries (Herrero et al., 2013; Zougmoré et al., 2018). As a result, livelihoods of 68% of households who earn income from livestock, more so dairy, are at risk. This is because dairy production is amongst the highest contributors of livestock income under mixed crop-livestock production systems which is common in developing countries. Developmental challenges and low adaptative capacity in Africa heightens the continent’s vulnerability (Tadesse and Dereje, 2018). Similarly, Kenya’s dairy industry, which is among the leading milk producers in Africa (Wilkes et al., 2020), faces severe threats from prolonged droughts and erratic weather patterns (Brandt, 2018). Therefore, uptake and utilization of dairy climate smart agriculture (CSA) practices is important for realizing resilient dairy production systems in developing countries. Such production systems have the potential to buffer farmers against climate change risks and sustain their livelihoods (Snapp et al., 2019).

Often, dairy farmers are faced with multiple climate change-induced burdens. These are decline in fodder quantity and quality, water scarcity, and increased incidences of parasites and diseases. They affect animal growth, reproduction and lactation performance, and also cause morbidity and mortality (FAO and New Zealand Agricultural Greenhouse Gas Research

Centre, 2017; Escarcha et al., 2018; FAO and GDP, 2018; Onyango et al., 2019; Maindi et al., 2020). Simultaneous occurrence of the effects necessitates change in uptake of dairy CSA practices to exploit the trade-offs and synergies, and achieve full environmental and economic benefits (Aryal et al., 2018).

Dairy CSA practices can be broadly categorized into improved fodder (nutrient rich feed, improved and drought tolerant fodder), fodder conservation (hay and silage), manure management (proper manure collection and storage, composting and use of biogas), health management through disease and parasites prevention and control, and animal husbandry (use of artificial insemination, culling less productive animals and use of improved breeds) (FAO and GDP, 2018; FAO and New Zealand Agricultural Greenhouse Gas Research Centre, 2017; Maindi et al., 2020). These practices have been promoted amongst dairy farmers in Kenya through interventions such as Kenya Climate Smart Agriculture Project and the Africa Milk Project (Onyango et al., 2019; Wairimu et al., 2022).

To cope with complex climate change risks, farmers often combine a number of dairy CSA practices as informed by synergies amongst the practices as substitutes, complements and or supplements. Nonetheless, variations in dairy farming systems as well as dairy farmers' socioeconomic characteristics affect the extent to which dairy farmers combine the different practices (Tittonell et al., 2010). As farmers seek to maximize benefits amidst varied opportunities and constraints in the context of their production system and characteristics, they exhibit heterogeneity in their dairy CSA practices uptake behavior. Consequently, dominance of dairy CSA practices can be exhibited across heterogenous farmer clusters. However, past research on dairy practices (Bechini et al., 2020; Didanna et al., 2018; Drewry et al., 2019; Kiggundu et al., 2021; Maindi et al., 2020; Mwanga et al., 2019; Okello et al., 2021; Yang et al., 2021) have mainly focused on intensity and factors influencing adoption. As such, dominant dairy CSA practices across heterogenous farmer clusters remain unknown. Further, implication of dominant practice(s) within a cluster on milk yield has not been well studied. This is despite milk yield being an immediate benefit that adopters would be keen on. This limits promotion of dairy CSA practices and could be linked to the current low uptake (Kirina et al., 2022; Nyasimi et al., 2017) in the country. Usually, 'one size fits all' approach is applied in promotion of CSA practices as it is economical cost-wise. However, it fails to acknowledge farmer differences as well as how dominance of certain practices could contribute to higher milk yield. Therefore, stratifying farmers into homogenous groups based on dominant dairy CSA practices could unearth a new perspective on uptake and inform tailored combinations of dairy CSA practices.

Farm typologies help bring meaning to complex and varied uptake of agricultural technologies (Collier et al., 2012; Tittonell et al., 2020). This is through maximization of heterogeneity across types and homogeneity within types (Weltin et al., 2017). In developing the typologies, farming households of similar characteristics are grouped into distinct types that are different from other emerging types. Typology could be functional, structural or both. Functional typology is inclined to systems behavior by organizing households into types based on the decisions they make. This is in addition to how they behave in response to stimuli such as constraints imposed by shocks or risks (Alvarez et al., 2014; Lopez-Ridaura et al., 2018;

Tittonell et al., 2020). Structural typology refers to inferred types using factors of production and production output variables. To add value to typology analysis, other variables are often used to predict membership to a type (Hammond et al., 2017). The typology approach has been extensively used to classify farming systems using diverse classification criteria depending on the research focus. The common application has been in characterizing farming systems mostly using structural variables (Hammond et al., 2017; Kuivanen et al., 2021; Musafiri et al., 2020). A few studies have linked such classifications to adoption of CSA practices (Amadu et al., 2020; Makate et al., 2018; Siddique et al., 2022). Nevertheless, such studies are limited (Hammond et al., 2020). Further, not much attention has been paid to characterization of dairy farming households particularly in explaining uptake of dairy CSA practices.

This study aimed at (i) delineating farmers into typologies of dominant dairy CSA practice(s) and, (ii) establishing the linkage of dairy CSA practices dominance to milk production. To address the study objectives, a typology approach was adopted to draw inferences from a sample size of 665 dairy farmers. Using 17 dairy CSA practices as indicator variables, latent class analysis (LCA) was used to determine typologies of dominant dairy CSA practices. The typologies were then subjected to one-way analysis of variance (ANOVA) to determine whether there were significant differences in milk yield across them. This was used as a measure of how dominance of practices across clusters influenced milk production. The study concludes by making policy recommendations on measures that could enhance dominance of dairy CSA practices and contribute to improved milk yield.

2. Methodology

2.2. Study area and sampling procedure

The study was undertaken in Kenya, which is among the countries with the largest dairy industry in Africa (Wilkes et al., 2020). The industry contributes to the country’s human, social, natural, physical, and financial capital (Abed and Acosta, 2018), important for economic growth. It is estimated that 4% of the overall gross domestic product (GDP) is from dairy (KDB, 2014). Besides, it is a source of livelihood to an estimated 3 million people; 1.8 million are in production and 1.2 million are employed in the other nodes of the value chain (KDB, 2021). The country is home to 22,853,225 heads of cattle (FAO, 2021) of which 18.82% are dairy (Waitituh, 2017). Dairy production is mainly practiced in the humid, sub-humid and semi-humid agroecological zones (Sombroek et al., 1982).

The study adopted multistage sampling design. Five counties; Uasin Gishu, Nakuru, Bomet, Nyeri and Nyamira were purposively selected. Their selection was informed by the high presence of exotic dairy cattle. Besides, the counties had been targeted for promotion of dairy CSA practices through Kenya Climate Smart Agriculture Project and Africa Milk Project (Onyango et al., 2019; Wairimu et al., 2022). The projects promoted a range of dairy CSA practices including those related to feed and fodder, manure management, animal health and husbandry. The technologies are in line with those identified as dairy related CSA practices (FAO and GDP, 2018; FAO and New Zealand Agricultural Greenhouse Gas Research Centre, 2017; Maindi et al., 2020). Additionally, the counties were linked to three dairy processors; Happy Cow Limited (HC), Wakulima Mukurueini Dairy Limited (WL) and New Kenya Cooperative Creameries factory in Sotik (NKCCS), which support milk marketing. Thus, it was envisaged that this market incentive would influence uptake of dairy CSA practices through income generated from milk sales.

In each county, major milk producing sub-counties targeted for Kenya Climate Smart Agriculture Project and Africa Milk Project interventions were identified. This resulted in purposive selection of Mathira West, Mukurwe-ini, Kieni East and Kieni West Sub-counties in Nyeri County, Njoro and Kuresoi South Sub-counties in Nakuru County, Ainapkoi Sub-county in Uasin Gishu, Manga and Borabu Sub-counties in Nyamira, and Chepalungu and Sotik Sub-counties in Bomet County. A ward from each sub-county was randomly selected. The lists of dairy farmers from the selected wards were obtained from the local administration or through the help of the cooperative extension officers. Systematic random sampling was thereafter used to select 665 farmers.

2.3. Typology analysis

Latent class analysis (LCA) was used to group farmers into typologies based on dominant dairy CSA practices. LCA uses underlying latent categorical variables which result in mutually exclusive and exhaustive latent classes in a population (Henry, 2006; Lanza and Rhoades, 2013). Membership to classes is not known a priori and is deduced from a set of observed variables. The empirical framework of LCA is modelled such that, let m_i represent element i of a response pattern m. An indicator function $Z(m_i = n_i)$ is established and equals 1 when the response variable $i = n_i$, and equals 0 otherwise. The probability of observing a particular vector of responses is given by Equation III,

$$K(M = m) = \sum_{c=1}^{C} \gamma_c \prod_{i=1}^{N} \prod_{n_i=1}^{N_i} \rho_{i,n_i[c}^{Z(m_i=n_i)} \qquad \text{(III)}$$

where γ_c is the probability of membership to class c, $\rho_{i,n_i[c}^{Z(m_i=n_i)}$ is the probability of a response n_i to item i conditional on membership to latent class c, γ parameters represent a vector of latent class membership probabilities that sum to 1 and ρ represents a matrix of item response probabilities conditional on latent class membership. Degrees of freedom are calculated as number of possible response patterns minus number of freely estimated parameters minus 1. Parameter estimation follows the expectation maximization (EM) algorithm.

In this study, LCA relied on 17 key dairy CSA practices (Table 1) as indicator variables which were dummy coded as 1 if a farmer had adopted and 0 otherwise. A threshold of 60% for the proportion of farmers in each cluster adopting a practice was used to determine dominance of a CSA practice across the clusters.

Table 1: Description of indicator variables used in the LCA

Practice	Description
Improved fodder	
Fodder Diversification (FD)	Cultivating and use of diverse high yield fodder
Drought Tolerant (DT)	Cultivation and use of fodder crops that can withstand drought
Leguminous Fodder (LF)	Production and use of high nitrogen fixing and high protein content legumes

Improved feed	
High Energy Concentrates (HEC)	Feeding milking cows with high energy concentrates proportional to their milk yield
Multi-nutrient Blocks (MB)	Feeding milking cows with nutrient-fortified blocks/feeds proportional to milk yield
Total Mixed Rations (TMR)	Preparing dairy feeds at home that are nutrient-balanced while incorporating locally available materials
Fodder conservation	
Treating Crop Residues (TCR)	Treating crop residues before feeding to enhance digestibility, unlock nutrients and improve nutrient content
Hay (HAY)	Baling harvested and cured fodder crops to preserve them for use during shortage
Silage (SIL)	Ensiling fodder crops to preserve them for use during shortage
Manure management	
Biogas (BIO)	Using cow dung to prepare biogas for household use and application of slurry to fodder crops
Covering Manure (CM)	Heaping or putting manure in a covered manure pit or heap
Composting (COM)	Composting manure and using it for fodder production
Health management	
Disease Prevention (DP)	Reducing disease burden through prevention techniques including vaccination and farm biosecurity measures
Disease Management (DM)	Managing diseases and parasites through timely treatment and appropriate use of animal drugs, and chemicals
Animal husbandry	
Artificial Insemination (AI)	Use of AI to get high yielding breeds
Adaptable Breeds (AB)	Rearing breeds adaptable to climatic conditions and farm characteristics
Culling (CUL)	Replacing less productive animals

3. Results

3.1. Socio-economic characteristics of the sampled dairy farming households

The sampled households were mainly headed by males at 83% (Table 3). On average, they attained 10 years of schooling, coinciding with primary level education implying low levels of education of smallholder farmers as reported by Okello et al. (2021). They had an average of 4.89 acres of land implying they were mainly smallholder dairy farmers. About 56% had security of land tenure while only 39.2% practiced intensive dairy production with an average milk yield of 7.13 liters/cow/per day with a liter fetching Kes. 39.5. The yield could be explained by the production system as it was close to those reported under open grazing and semi-zero grazing dairy production systems with daily milk yield averages of 6.5 to 7 liters and 6.6 liters respectively (Tegemeo Institute of Agricultural Policy and Development, 2021). The households belonged to an average of 1 group (81.1%) of which 74.3% were legally registered. On average, the households had received 4 extension visits in the last 1 year. They accessed extension from multiple dairy CSA extension service providers; 53.7% accessed from government, 71.6% from private, 7.15 from NGOs and 45.95 from FOs, in line with the pluralistic extension delivery system. About 11.9% had access to financial credit while 52% had non-farm off-farm income allowing them to supplement income from dairy and other farming activities. The results showed that about half (51.6%) were aware about climate change (causes, extreme events and effects). On average, the households had adopted about 5 of the 17 dairy CSA practices studied. This implied low adoption similar to findings of earlier study by Nyasimi et al. (2017).

Table 2: Socio-economic characteristics of the sampled dairy farming households

Variable	Mean
Sex (male)	0.83
Education level (years)	10.40
Total farm size (acres)	4.89
Security of land tenure (title)	0.56
Dairy production system (intensive)	0.39
Risk attitude (risk averse)	0.67
Milk yield (liters/cow/day)	7.13
Average milk price (Kes/Liter)	39.53
Number of dairy groups (Number)	1.13
Dairy group legality (Registered)	0.74
Number of extension visits (Number)	4.02
Government extension provider (Government)	0.54
Private extension provider (Private)	0.72
NGO extension provider (NGO)	0.07
FO extension provider (FO)	0.46
Financial credit access (yes)	0.12
Having non-farm off-farm income (yes)	0.52
Awareness about climate change (aware)	0.52
Number of dairy CSA practices adopted (Number)	5.21

3.2. Typologies of dominant dairy CSA practices

3.2.1. Model fit

There are various fit statistics that can be used to determine model fit Latent Class Analysis. The most common are Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as they are able to balance between accuracy and overfitting (Sinha et al., 2021). For both, the class with the lowest ICs indicate better fit (Sinha et al., 2021; Weller et al., 2020). Although both penalizes model as the number of parameters increase, for BIC the penalty is higher as the sample size increases and favors fewer classes (Sinha et al., 2021). In addition to fit statistics, Weller et al. (2020) emphasizes on interpretability of the results. Therefore, considering the interpretability of the results and the study sample size, the Akaike Information Criterion (AIC) instead of the Bayesian Information Criterion (BIC) was used to determine the number of classes that best explain the typologies. The Bayesian Information Criterion (BIC) gave only two classes whose interpretability was limiting in the context of dominant dairy CSA practices and the sample size of 665 was considered large thus increasing the penalty (Table 2). The process began with two classes until AIC began to increase such that the output with the lowest AIC was selected in line with Tittonell et al. (2020).

Table 3: Latent class model fit statistics (N= 665)

	2 classes	3 classes	4 classes	5 classes	6 classes
AIC	9942.00	9875.59	9855.73	9837.25	9838.72
BIC	10099.49	10114.07	10175.22	10237.73	10320.20
G^2 (Likelihood ratio/deviance statistic)	2269.35	2166.94	2111.08	2056.60	2022.07
X^2 (Chi-square goodness of fit)	72589.64	56954.49	51509.31	51283.60	39881.44
No. of estimated parameters	35.00	53.00	71.00	89.00	107.00
Residuals degrees of freedom	630.00	612.00	594.00	576.00	558.00
maximum log-likelihood	72589.64	-4884.79	-4856.87	-4829.62	-4812.36

3.2.2. Typologies derived from dominant dairy CSA practices

The study results identified 5 typologies (Table 3) with homogenous characteristics based on the dominant dairy CSA practices. The resulting dairy household typologies were: health management dominated typology (Typology 1), health and animal husbandry dominated typology (Typology 2), health, animal husbandry, manure and improved feed dominated typology (Typology 3), health, animal husbandry, improved feed and fodder dominated typology (Typology 4), health, animal husbandry, improved feed and fodder and fodder conservation dominated typology (Typology 5). Dominant practices varied across typologies corroborating findings by Douxchamps et al. (2016) that showed varied uptake of CSA practices across household types. There was an increase in number of dominant practices as typologies progressed from 1 to 5. Where they had equal number of dominant practices, the practices were in distinct categories. Dominance of several practices within a typology is an indication that farmers do not rely on one technology to cope with climate change but rather seek to combine several practices.

The majority (31.6%) of the households were in Typology 2, dominated by use of DM and AI; practices linked to health and animal husbandry management. Approximately 91% and 60% of the households in this typology practiced DM and AI respectively. The Typology 1 households comprised 19.4% of the sampled households. Similar to Typology 2, it was dominated by only two practices although under health management category. Dominant practices were DP (87%) and DM (97%). Both typologies 1 and 2 constituted 51% of the households implying low uptake of dairy CSA practices. This is consistent with the findings by Maindi et al. (2020) and

Okello et al. (2021) who found that majority of the households had taken up few dairy technologies.

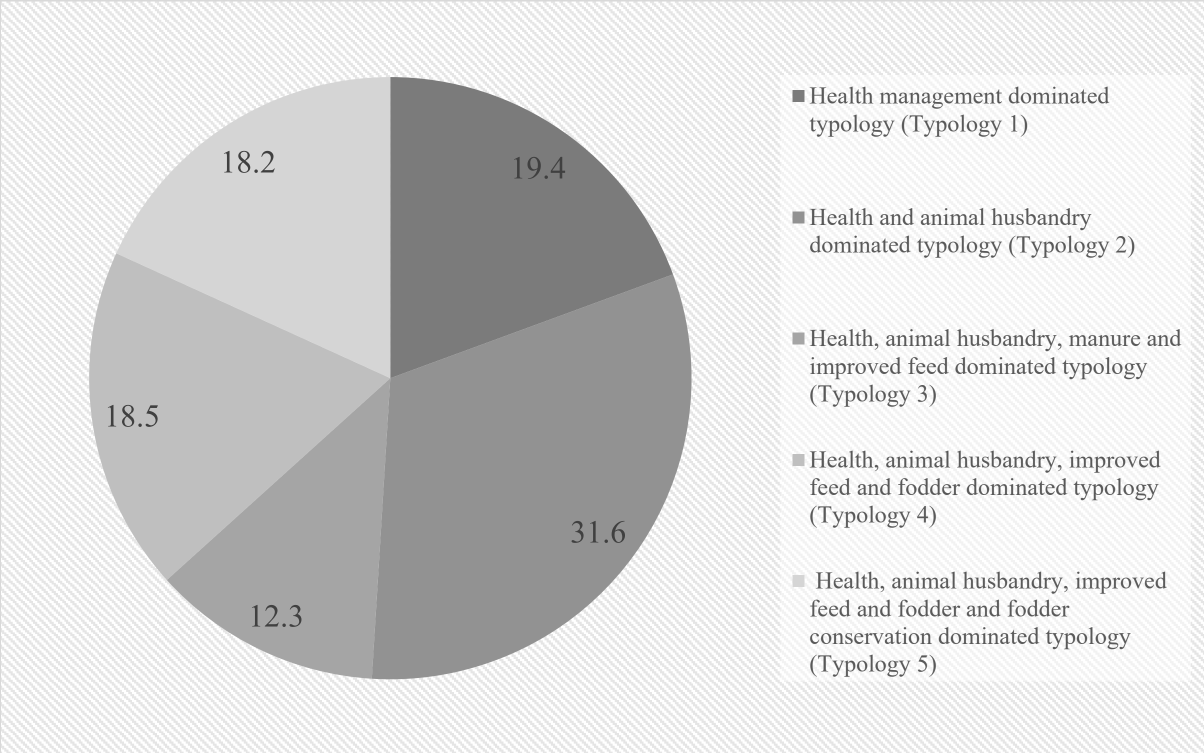

Figure 1: Households membership to typologies of dominant dairy CSA practices

Typology 4 ranked third on percentage of sampled households at 18.5%. It was dominated by multiple dairy CSA practices related to health, animal husbandry and improved feed and fodder; DM, DP, AI, HEC and FD. All households had adopted DM, 94% DP, 86% HEC and 84% AI. Further, over half (61%) had adopted FD. Low dominance of fodder conservation practices distinguished this typology from Typology 5.

Typology 5 was made up of 18.2% of the households. They demonstrated dominance of multiple dairy CSA practices cutting across several categories; health, animal husbandry, improved feed and fodder and fodder conservation. A high proportion produced diverse fodder (FD) (71%), used HEC (87%) and conserved fodder (HAY at 68% and SIL at 68%). Majority were equally keen on improving their breeds (AI at 83%) and managing diseases (DM at 93%). In concurrence with Maindi et al. (2020), utilization of AI under Typology 5 was complemented with use of HEC as well as fodder conservation (HAY and SIL). This indicated practices interdependencies demonstrating their complementarity and likelihood of deriving benefits from having multiple dominant dairy CSA practices. The typology dominated by health, animal husbandry, manure management and improved feed (Typology 3), had the least number of households (12.33%). All households in this typology were practicing COM, 87% were using HEC, 94% were seeking to improve their breeds through AI and practiced animal health management through DP (80%) and DM (100%). Dominance of practices under this typology depicted similarities to those of Typology 4 except that this typology was also dominated by COM while Typology 4 by FD.

Notably, across typologies, DM was the most dominant practice followed by AI for typologies 2,3,4 and 5 and DP for typology 1, findings consistent to those of Okello et al. (2021). Over half of the practices (58.8%) were least dominant and included manure management practices (BIO, CM, COM), DT, LF, TCR, TMR, MB, AB and CUL. Their low dominance could be linked to their unavailability, lack of awareness or cost constraints.

Table 4: Typologies of dominant dairy CSA practices

Dairy CSA practices		**Marginal means**			
	Health management dominated typology (Typology 1)	Health and animal husbandry dominated typology (Typology 2)	Health, animal husbandry, manure and improved feed dominated typology (Typology 3)	Health, animal husbandry, improved feed and fodder dominated typology (Typology 4),	Health, animal husbandry, improved feed and fodder and fodder conservation dominated typology (Typology 5).
FD	0.20	0.40	0.21	**0.61**	**0.71**
DT	0.21	0.11	0.12	0.20	0.27
LF	0.00	0.07	0.14	0.08	0.25
HEC	0.37	0.42	**0.87**	**0.84**	**0.87**
MB	0.09	0.00	0.16	0.13	0.21
TCR	0.11	0.03	0.00	0.00	0.40
TMR	0.00	0.00	0.04	0.05	0.12
HAY	0.19	0.29	0.33	0.23	**0.77**
SIL	0.00	0.19	0.17	0.11	**0.68**
BIO	0.00	0.01	0.00	0.01	0.14
CM	0.17	0.12	0.00	0.23	0.18
COM	0.23	0.13	**1.00**	0.00	0.34
DP	0.**87**	0.25	**0.80**	**0.94**	**0.69**
DM	0.**97**	**0.91**	**1.00**	**1.00**	**0.93**
AI	0.21	0.**60**	**0.94**	**0.86**	**0.83**
AB	0.25	0.04	0.36	0.46	0.36
CUL	0.05	0.01	0.08	0.09	0.14
Class membership (%)	19.40%	31.58%	12.33%	18.50%	18.20%

Fodder Diversification (FD), Drought Tolerant (DT), Leguminous Fodder (LF), High Energy Concentrates (HEC), Multi-nutrient Blocks (MB), Treating Crop Residues (TCR), Total Mixed

Rations (TMR), Hay (HAY), Silage (SIL), Biogas (BIO), Covering Manure (CM), Composting (COM), Disease Prevention (DP), Disease Management (DM), Artificial Insemination (AI), Adaptable Breeds (AB), Culling (CUL)

3.3. Analysis of milk yield variations across the typologies of dominant dairy CSA practices

Average milk yield differed across the typologies with Bartlett's test for equal variances being statistically significant (Prob>chi2 = 0.000). Typology 5 had the highest milk yield of 8.22 liters per cow per day with a positive deviation of 1.09 liters from the overall milk yield average of 7.13 liters (Table 5). The high milk yield could be attributed to the typology having the highest number of dominant dairy CSA practices particularly fodder conservation practices (HAY and SIL) which distinguished it from Typology 3 which had the second highest milk yield average. Fodder conservation practices help address fodder deficiencies and seasonality enabling the households to sustain their milk yield resulting in higher overall milk yield averages. The results concur with those of Sakwa et al. (2021) who linked fodder conservation to increase in milk yield.

The second highest milk yield was realized by households under Typology 3 with an average of 8.02 liters per cow per day. Typology 2 milk yield (7.13 liters) equaled the overall average. Contrary to expectations, Typology 4 realized just about average milk yield despite having same number of dominant dairy CSA practices to those of Typology 3. However, Typology 3 was distinct since all households in this typology practiced COM. Composting is a soil fertility enhancement measurer that could support fodder production and improve fodder yield contributing to enhanced milk yield.

The milk yield average for Typology 1 had a deviation of -1.55 liters per cow per day from the overall average and was the lowest across all the typologies. Unlike other typologies, AI was not dominant perhaps explaining the level of milk yield which concurs with findings of Saha and Bhattacharyya (2021) linking AI to increase in milk yield. This explains an important role of AI in realization of improved milk yield through improved animal genetic make up.

Table 5: Average milk yield (litres/cow/day) of typologies derived from dominant dairy CSA practices

Typology	**Mean milk yield (litres/cow/day)**	**Rank in terms of milk production**
Health management dominated typology (Typology 1)	5.58	5
Health and animal husbandry dominated typology (Typology 2)	7.13	3
Health, animal husbandry, manure and improved feed dominated typology (Typology 3)	8.02	2
Health, animal husbandry, improved feed and fodder dominated typology (Typology 4),	7.08	4

Health, animal husbandry, improved feed and fodder and fodder conservation dominated typology (Typology 5)	8.22	1
Overall (sample) milk yield average	7.13	-

4. Conclusions and policy implications

The study classified farmers into typologies based on dominance of the 17 dairy CSA practices studied. Five typologies – health management dominated typology (Typology 1), health and animal husbandry dominated typology (Typology 2), health, animal husbandry, manure and improved feed dominated typology (Typology 3), health, animal husbandry, improved feed and fodder dominated typology (Typology 4), and health, animal husbandry, improved feed and fodder and fodder conservation dominated typology (Typology 5) were identified. Majority of the households (51%) were in Typology 1 and Typology 2, indicating low dominance of most dairy CSA practices. Further, a high number (58.8%) of the practices were least dominant across the typologies. They included manure management practices (BIO, CM, COM), DT, LF, TCR, TMR, MB, AB and CUL. Awareness creation about these practices could help enhance their uptake. Future research should consider further analysis of factors deterring their uptake.

As typologies progressed from 1 to 5, dominant practices increased. Besides, the dominant practices varied across typologies. Typologies 1 and 2 had the least number though with variations of dominant practices. Unlike Typology 1, Typology 2 dominant practices cut across two categories of dairy CSA practices; health and animal husbandry management. Similarly, typologies 3 and 4 had equal number but varied dominant dairy CSA practices. While HEC, DM, DP and AI were common for the two typologies, Typology 3 was also dominated by COM and Typology 4 by FD. Typology 5 had the highest number (7) of dominant dairy CSA practices. Co-benefits from high dominance of dairy CSA practices was evident for Typology 5 which had the highest average milk yield. Certain dairy CSA practices were attributed to higher milk yield; COM for Typology 3 and HAY and SIL for Typology 5. Composting (COM) is important in facilitating production of fodder and that of fodder conservation practices (HAY and SIL) in addressing fodder shortage and seasonality. In this regard, there is need to emphasize uptake of these practices among dairy farmers as they can assure them of higher milk yield amidst climate change effects.

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