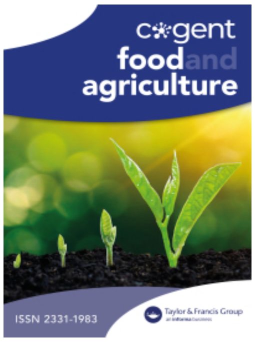

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ANIMAL HUSBANDRY & VETERINARY SCIENCES | RESEARCH ARTICLE

Milk somatic cell count, composition and yield of multi-breed dairy cattle in Ethiopia

Tegegn Fantahun Chernet[a,b], Okeyo Mwai[c], Selam Meseret[d], Enyew Negussie[e], Raphael Mrode[c,f], Getinet Mekuriaw Tarekegn[a,f], Zewdu Edea[b], Gebregziabher Gebreyohanes[c], Chinyere Ekine-Dzivenu[c], Asrat Tera[g] and Tesfaye Sisay Tessema[h]

[a]Animal Biotechnology Department, Institute of Biotechnology, Addis Ababa University, Addis Ababa, Ethiopia; [b]Animal Biotechnology, Genomics and Bioinformatics Department, Bio and Emerging Technology Institute, Addis Ababa, Ethiopia; [c]Livestock Genetics Department, Africa Asia Dairy Genetic Gains program, ILRI, Nairobi, Kenya; [d]Livestock Genetics Department, Africa Asia Dairy Genetic Gains program, International Livestock Research Institute (ILRI), Addis Ababa, Ethiopia; [e]Animal Genomics and Breeding Department, Natural Resources Institute (Luke), Finland; [f]Animal and Veterinary Department, Scotland's Rural College, Edinburgh, United Kingdom; [g]Animal Genetic Improve and Research Department, Livestock Development Institute, Addis Ababa, Ethiopia; [h]Health Biotechnology Department, Institute of Biotechnology, Addis Ababa University, Addis Ababa, Ethiopia

ABSTRACT
Mastitis is highly prevalent and causes significant economic loss in the Ethiopian dairy industry. An important aspect of monitoring dairy cow health and milk quality is understanding somatic cell count (SCC), composition and milk yield. This study aimed to evaluate milk SCC, composition, yield, and factors associated with the quality traits of Ethiopian dairy farms. A total of 3269 milk samples were collected from 1719 cows across 201 herds. The overall means and standard deviations of $\log_e$-transformed somatic cell score (SCS), fat, protein, lactose, and test day milk yield were 12.39±1.61 cells/mL, 2.68±1.71%, 3.17±0.24%, 4.75±0.36%, and 10.45±5.04 litres, respectively. The results showed that 40.7% of the analysed milk samples had the SCC class ≤ 200x103 cells/mL. SCS was negatively correlated with milk yield and composition but moderately positively correlated with electrical conductivity ($r=0.41$). Lactation stage, breed, parity, herd size and altitude significantly influenced most milk parameters, except fat content, which was unaffected by parity ($p>0.05$). In conclusion, the highest SCS was recorded in this study. An increase in SCS negatively affects both milk yield and composition. Therefore, breed selection and herd management should focus on reducing the SCC to improve milk yield and quality.

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1. Introduction

Dairy production and demand for milk are increasing markedly in developing countries (Adesogan & Dahl, 2020). Despite having the largest cattle population in Africa, 66 million (CSA, 2022) and 29 indigenous cattle breeds or ecotypes (Domestic Animal Diversity Information System (DAD-IS), 2023). In Ethiopia, the dairy system is characterized by low production and productivity. Decades have been spent on genetic improvement of dairy cattle through selection and crossbreeding. However, the genetic improvement program is progressing slowly, and the number of crossbred populations is not more than 5% (CSA, 2022). There is a large productivity gap to meet the expanding demand; as a result, the per capita milk consumption in Ethiopia has been low (FAO & NZAGRC, 2017; Yilma et al., 2017).

Milk yield per cow has increased globally, partly due to genetic selection, improved nutrition and better management. Nonetheless, it has a profound effect on the health, fertility and welfare of dairy cattle (Barkema et al., 2015). Mastitis is one of the most common health problems in high-production dairy breeds, causing huge economic losses in the dairy industry (FAO, 2014). An increase in somatic cell count (SCC) negatively affects milk yield and composition (Cinar et al., 2015; Malek dos Reis et al., 2011).

CONTACT Tegegn Fantahun Chernet tegefanta@yahoo.com Animal Biotechnology Department, Institute of Biotechnology, Addis Ababa University, Addis Ababa, Ethiopia

SCC is used as a key indicator for detecting mastitis in dairy cattle, with a threshold of $\leq 200 \times 10^3$cells/mL used to define a healthy mammary quarter (Bobbo et al., 2020; Hisira et al., 2023; IDF, 2013). However, some studies recommended lowering this limit to $\leq 100 \times 10^3$cells/mL, as higher values may signal potential udder health problems (Sumon et al., 2020; Zhang et al., 2022). Milk quality traits and yield are influenced by factors such as breed, animal physiology, feed and climatic conditions (Cheruiyot et al., 2018; Magro et al., 2023; Tao et al., 2018). Many countries have regulations that govern milk quality, with pricing based on milk composition and SCC (Alhussien & Dang, 2018; IDF, 2013). However, in sub-Saharan Africa, the testing and regulation of milk quality are inconsistently enforced (Özkan Gülzari et al., 2020). In Ethiopia, milk and dairy products are sold without pricing based on quality for consumers. Although dairy cattle herd performance recording and advisory services for farmers were introduced a decade ago, milk quality traits were not initially included in these schemes. Recently, the African Asian Dairy Genetic Gains (AADGG) program has been implemented to record national dairy cattle performance and incorporate SCC and milk composition into routine evaluation for selected herds (AADGG, 2023). Despite these initiatives, there is limited information on the SCC and milk composition of multibreed dairy cattle across Ethiopia's diverse production environments.

An important aspect of monitoring the health and milk quality of dairy cows is to understand their SCC, composition and yield. Several studies have reported that the prevalence of subclinical mastitis in lactating dairy cows in Ethiopian farms ranges from 28.34% to 62% (Abebe et al., 2016; Getaneh & Gebremedhin, 2017; Tezera & Aman Ali, 2021). Previous research (Kebede, 2018; Mesfin & Getachew, 2007; Tegegne & Tesfaye, 2017; Yoseph et al., 2022; Zebib et al., 2023) has focused on bacteriological milk quality and composition in smallholder dairy cattle. However, studies estimating SCC, composition, and comparisons different breeds across larger geographic regions are scarce. Most of these studies have not fully explored the relationship between milk SCC and composition traits. To our knowledge, no comprehensive reports exist on the overall milk SCC, composition and yield, and the factors influencing these traits in multibreed dairy cattle in Ethiopian herds. Such information is crucial for helping farmers adopt better management practices to improve productivity and control mastitis. Therefore, the objective of this study was to determine the milk SCC, composition, yield and the genetic and nongenetic factors that affect these traits in Ethiopian dairy farms.

2. Materials and methods

2.1. Study area and design

This study was conducted in dairy farms owned by smallholder, commercial operations, governmental institutions and universities registered under scheme of the Africa Asia Dairy Genetic Gain project (AADGG, 2023). In total, 201 randomly selected dairy farms from different locations across Addis Ababa City Administration, Oromia, Amhara, South Ethiopia, Central Ethiopia, Sidama, and Southwest People's Regional States of Ethiopia were included (Figure 1). The study population consisted of 1795 lactating cows with diverse genetic backgrounds, all of which had a national identification ear tags and had calved five days prior to the actual sampling date. A total of 3588 milk samples were collected and analysed from July 2021 to May 2023.

A test-date milk sampling approach was used, and the farms were visited once to three times on monthly base during the study period. The seasons of the study area were classified according to the National Meteorology Agency (NMA) of Ethiopia (NMA, 2023) into three categories: i) the long rainy season (June to September), ii) the dry season (October to January), and iii) the short rainy season (February to May).

2.2. Ethics approval

This study was conducted with the approval of the Institutional Review Board of the College of Natural and Computational Sciences, Addis Ababa University, under approval reference number CNCSDO/513/15/2023. All animals were handled by experienced milkers, and no-invasive milk sampling techniques were used. The research adhered to the ARRIVE guidelines.

2.3. Consent and permission

The dairy farm owners selected for this study were voluntary participants in the AADGG program. The purpose and nature of the study were explained to them verbally, considering the literacy levels of the population involved. They were informed that they could withdraw at any time without any consequences either before or during their participation. Verbal consent was obtained using a smartphone sound recorder application. The decision to opt for verbal consent with recording was reviewed and approved by the

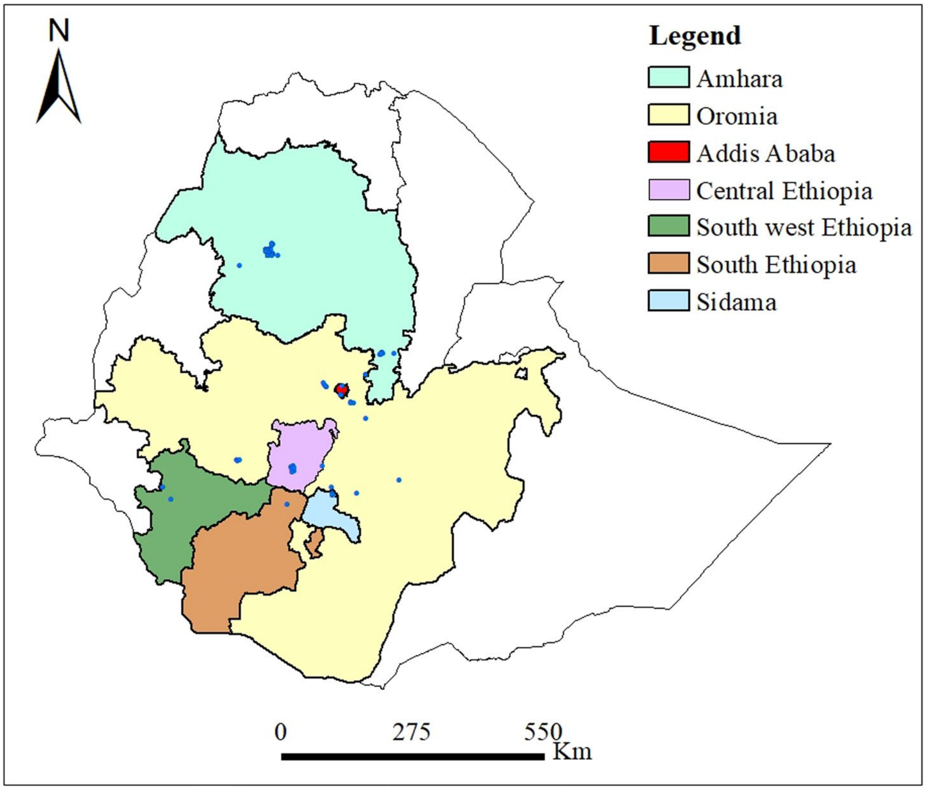

Figure 1. The distribution of sampled dairy farms (map created by authors using QGIS V 3.30) (QGIS, 2023).

Institutional Review Board of the College of Natural and Computational Sciences, Addis Ababa University (approval number CNCSDO/513/15/2023). The study commenced only after obtaining the participants' verbal permission for milk sampling and the collection of other necessary information.

2.4. Breed and genetic group of cattle in the study area

Cattle of different breeds and admixture levels were raised on the selected dairy farms. The most common were Holstein crossbreeds (with local cattle breeds with known and unknown admixture levels). Additionally, there were crosses between Ethiopian Boran cattle and Holstein (50% Boran and 50% cross), pure Jersey, and limited crosses of Jersey and local cattle (Sheko, and Fogera) breeds were found in the dairy farms. Crossbred cattle in Ethiopia dairy farms exhibited different proportions of the exotic dairy genetics, with an average of 72%, including 36% Friesian and 30% Holstein (Gebrehiwot et al., 2020).

2.5. Herd management

In the herds studied, milking was performed twice a day using hand milking, except in 1.0% of the dairy farms where machine milking was practiced. Calf sucking was uncommon, observed in only 2.5% of farms. Teat-dipping for udder health monitoring in both lactating and dry cows was also rare. All farms practiced stall-feeding, though a few allowed their cattle to graze on natural pastures during the day and provided supplemental feed in barns, especially during milking. The feed offered in the studied dairy farms was heterogenous, with cattle being fed a variety of feedstuffs such as green forages, grass hay, crop residues, concentrates (commercial mixes) and agro-industrial by-products. Brewer wastes or other by-products were commonly used as supplemental feed for lactating cows. However, feed supply was insufficient, and feeding practice generally did not account for milk yield, physiological status or body condition of the cows. Housing and husbandry practices varied across the sampled herds. The number of lactating cows on each farm during sampling ranged from 1 to 72. Milk was sold by volume, without consideration of composition or quality. For this study, farms were categorized purposively based on the number of milking cows present at the time of sampling, without counting number of dry cows, heifers and calves, and classified as small, medium and large herds, with 1–5, 6–14, and ≥ 15 lactating cows, respectively (FAO & NZAGRC, 2017).

2.6. Milk sample collection

Before collecting milk samples, cows' udders and teats were washed with clean water to remove any dirt. Teats were then dried with individual towels to ensure aseptic milk collection. During sample collection, the cows' udder health (including any sign of pain, inflammation, swelling, fibrosis, redness, visible injury or lesion, tissue atrophy and teat blindness) and the gross milk characteristics (such as the presence of blood spots, clots, flakes or other consistency changes) were recorded. Prior to sampling, the first 3–4 streams of milk were discarded. A 30–40 mL composite milk sample was then taken from all non-blind cow teats using a sterile 50 mL bottle, labelled with the cow's ID. Samples were collected during regular milking times, in both morning and evening, with the majority (87.9%) collected in the evening. The sampling date and milk yield were recorded at the time of sample collection. The fresh milk samples were transported in an ice box with ice cubes for analysis.

2.7. Laboratory analysis

Fresh milk samples were examined for SCC and milk composition within 6 hours of collection. The raw milk sample, contained in a test tube, was thoroughly mixed by placing the tips of the containers in a Mini Vortex mixer for 1–2 seconds, repeating 3–4 times without allowing the sample to reach the cap. Using an automatic pipette with a new sterile tip, 100 µL of the raw milk sample was pipetted into a microtube containing SOFIA GREEN lyophilized dye. The Eppendorf tube containing the dye and milk sample was gently stirred for 1–2 seconds, repeated 8–9 times, taking care not to let the solution reach the cap. The sample was then incubated with the dye for at least 1 minute but no longer than 10 minutes. After incubation, 8 µL of the thoroughly mixed sample was pipetted into the microfluidic camera of the LACTOCHIP x4, ensuring no bubbles formed. The loaded LACTOCHIP x4 was placed into the cartridge of the LACTOSCAN SCC by holding the side edges, and within 1 minute, and analysis was performed using the embedded software system.

Subsequently, the device software was switched to compositional analysis. To ensure no milk fat residues remained on the tube cap or sides, the sample tube was mixed using a Mini Vortex mixer, and then up to 20 mL the milk sample was aspired into the device for analysis. The machine measured the milk's protein (%), lactose (%), fat (%), solid-not-fat (%), total solids (%), salts (minerals) (%), electrical conductivity (mS/cm) and density (kg/m^3). The analysis was conducted using somatic cell counting (Lactoscan SCC) and an ultrasonic milk analyser (Lactoscan MCCW), both integrated into a single device, following the protocol from the Bulgaria manufacturer (Milkotronic Ltd, 2017).

2.8. Statistical analysis

Milk SCC, test day milk yield, composition, farm location (GPS coordinates) and basic lactating cow information (including birth date, breed, parity, age, sampling and calving date) were retrieved from the ADGG database (https://portal.adgg.ilri.org/). After cleaning the raw data to remove incorrect or outlier records, 1719 cows and 3269 valid records were retained for further analysis. Since SCC was non-normally distributed, it was log$_e$ transformed to somatic cell score (SCS) using the equation SCS= log_e (SCC), following Mrode et al. (2012). Similarly, fat content which was also non-normally distributed was transformed log$_e$ transformed as Fat$_t$=log_e(Fat + 1). Non-normal distributed fat data was reported and transformed by Cheruiyot et al. (2018). SCC values were grouped into six categories: ≤ 50×10^3, 51–200×10^3, 201–350×10^3, 351–500×10^3, 501–999×10^3, and ≥1000×10^3 cells/mL to fit as fixed effects on milk composition and yield customized from the work of Ebrahimie et al. (2018; Guo et al., 2010). Furthermore, cows were classified into three health statuses based on their SCC: healthy, subclinical mastitis (SCM) and clinical mastitis (CM) with their SCC values of up to 200×10^{3}cells/mL, between 200 to 500×10^{3}cells/mL and above 500×10^{3}cells/mL, respectively, following Alhussien & Dang (2018) and IDF (2013).

All statistical analyses were performed using R for statistical computing, version 4.2.2 (R Core Team, 2022). Descriptive statistics, frequency distribution and Pearson's correlation analyses were performed. General linear models (GLMs) were fitted for milk SCS (Model 1) and milk composition and yield (Model 2). The fitted GLM was analysed using the sasLM package (Sunwoo et al., 2020) and significant lsmean values ($p<0.05$) were separated using the Tukey method.

Model 1 can be represented

$$y_{ijklmno} = \mu + B_i + P_j + L_k + S_l + A_m + H_n + e_{ijklmno} \quad (1)$$

where $y_{ijklmno}$ is the SCS content measurement of o^{th} individual animal, µ is the overall mean, B$_i$ is the

Table 1. Overall SCS, SCC, milk yield and composition traits of dairy cows in Ethiopia.

Variables	N	Mean	Min	Max	SD
SCS (cells/mL)	3269	12.39	7.23	16.1	1.61
SCC (cells/mL)	3269	657367.2	1387	9865244	1019252
Fat (%)	3269	2.68	0.5	9.78	1.71
Lactose (%)	3269	4.76	3.77	6.61	0.36
Protein (%)	3269	3.17	2.52	4.36	0.24
SNF (%)	3269	8.65	6.87	12.0	0.64
Salt (%)	3269	0.70	0.5	0.97	0.05
TS (%)	3269	11.32	7.44	20.12	1.93
EC (mS/cm)	3269	6.06	3.91	13.90	1.01
Density (kg/m^3)	3269	1030.4	1005.5	1042.6	2.70
MY (L)	3269	10.45	1.5	31	5.04

SCS (somatic cell score), Logarithmic values of SCC (somatic cell count); EC, Electrical conductivity in millisiemens per centimeter (mS/cm); TS, total solids; SNF, solids-not-fat; MY, milk yield; SD, standard deviation; N, number of milk sample tested; Min, minimum; Max, maximum.

fixed effect of i^{th} breed type (i is HFC(Holstein crossbreed with different local cattle breeds), BHFC (50% Boran and 50% Holstein cross), Jersey, and Local (Sheko and Fogera cattle), P_j is the fixed effect of j^{th} parity (j is 1, 2, 3 and ≥4), L_k is the fixed effect of the k^{th} stage of lactation (k is 5–60 (early), 61–180 (mid), 181–305 (late) and >305 (extended) days in milk (DIM)), S_l is fixed effects of the l^{th} sampling period (l is long rainy, dry and short rainy seasons), A_m is the fixed effect of the m^{th} altitude range (m=1232–1600 m, 1601–2300 m, and >2300 m), H_n is the fixed effect of the n^{th} herd size (n is small, medium and large), and $e_{ijklmno}$ is the random residual term ~ N (0, σ2e).

Model 2 can be represented as follows:

$$y_{ijklmnop} = \mu + B_i + P_j + L_k + S_l + A_m + H_n + C_o + e_{ijklmnop} \tag{2}$$

where $y_{ijklmnop}$ is the milk composition and yield content record of p^{th} animal, C_o is the fixed effect of o^{th} SCC class (o=6 classes: ≤ 50x10^3, 51–200 × 10^3, 201–350 × 10^3, 351–500 × 10^3, 501–999 × 10^3, and ≥1000 × 10^3), $e_{ijklmnop}$ is the random residual term ~ N (0, σ^2e), and all other fixed effects are defined in Model 1.

3. Results

3.1. Summary statistics of milk SCS, composition and yield

Overall, milk samples from dairy cows in Ethiopian farms had an average of 12.39 ± 1.61 cells/mL SCS, 657367.2 ± 1019252 cells/mL SCC, 4.76 ± 0.36% lactose, 3.17 ± 0.24% protein and 2.68 ± 1.73% fat contents (Table 1). Variations in the milk yield and quality by SCC class, based on univariate analysis, are shown in Table 2. Milk composition and yield significantly decreased in the SCC class ≥ 501x10^3 cells/mL compared to those with SCC ≤ 200x10^3 cells/mL. Only 40.7% of the analysed milk sample fell within the SCC class ≤ 200x10^3 cells/mL.

Table 2. Variations in the milk yield and quality in relation to SCC class.

Constituents	Healthy	Subclinical mastitis	Clinical mastitis
SCC (cells/ml)	<2x10^5	2–5 x10^5	>5 x10^5
N	1332	852	1085
Lactose (%)	4.84 ± 0.35^{a}	4.78 ± 0.35^{b}	4.66 ± 0.35^{c}
Protein (%)	3.22 ± 0.23^{a}	3.18 ± 0.23^{b}	3.10 ± 0.23^{c}
Fat (%)	2.8 ± 1.71^{a}	2.59 ± 1.61^{b}	2.62 ± 1.77^{b}
SNF (%)	8.78 ± 0.63^{a}	8.68 ± 0.63^{b}	8.47 ± 0.63^{c}
Salt (%)	0.71 ± 0.05^{a}	0.71 ± 0.05^{b}	0.69 ± 0.05^{c}
TS (%)	11.58 ± 1.95^{a}	11.25 ± 1.83^{b}	11.07 ± 1.96^{b}
EC (mS/cm)	5.65 ± 0.73^{a}	6.00 ± 0.78^{b}	6.61 ± 1.19^{c}
Density (kg/m3)	1030.8 ± 2.6^{a}	1030.6 ± 2.7^{a}	1029.8 ± 2.7^{b}
MY (L)	10.89 ± 5.22^{a}	10.64 ± 5.02^{a}	9.77 ± 4.76^{b}

^{a,b,c}Within a row, means with different letters differ significantly ($p < 0.001$); N, number of milk samples tested; SCC, somatic cell count; EC, electrical conductivity in milliiemens per centimeter (mS/cm); TS, total solids; SNF, solids-not-fat; MY, milk yield.

3.2. Association of SCS with composition and milk yield

The correlation coefficients between milk yield, composition and SCS are described in Table 3. The absolute value of the correlations between milk components ranged from 0.44 to 0.99. SCS was significantly negatively correlated with the analysed milk parameters ($p < 0.001$), except for EC ($r = 0.42$).

3.3. Effects of parity

As shown in Table 4, most of the analysed milk parameters were significantly affected by parity, except for fat percentage ($p > 0.05$). First-parity cows had the lowest SCS and EC contents in their milk ($p < 0.01$). Similarly, cows with parity ≥ 4 showed the lowest percentage of lactose, protein, SNF, salt and density. Milk yield increased from primiparous to multiparous cows.

Table 3. Correlation coefficients of SCS with milk yield and composition traits.

Traits	Fat[1]	MY	Density	Lactose	Protein	SNF	Salt	TS	EC
SCS	-0.06^{***}	-0.10^{***}	-0.14^{***}	-0.18^{***}	-0.18^{***}	-0.18^{***}	-0.19^{***}	-0.12^{***}	0.42^{***}
Fat		-0.26^{***}	-0.34^{***}	0.23^{***}	0.14^{***}	0.20^{***}	0.20^{***}	0.91^{***}	-0.21^{***}
MY			0.12^{***}	-0.03^{ns}	-0.01^{ns}	-0.03^{ns}	-0.03^{ns}	-0.23^{***}	-0.07^{***}
Density				0.78^{***}	0.83^{***}	0.79^{***}	0.79^{***}	-0.06^{***}	-0.28^{***}
Lactose					0.99^{***}	0.99^{***}	0.99^{***}	0.52^{***}	-0.43^{***}
Protein						0.99^{***}	0.99^{***}	0.45^{***}	-0.43^{***}
SNF							0.99^{***}	0.5^{***}	-0.44^{***}
Salt								0.5^{***}	-0.44^{***}
TS									-0.32^{***}

***, highly significant correlations ($p < 0.001$); ^{ns}, not significant ($p > 0.05$), SCS, somatic cell score; MY, milk yield; Fat[1], $\log_e$- transformed fat percent; TS, Total solids; SNF, Solids-not-fat; EC, Electrical conductivity in millisiemens per centimeter (mS/cm).

Table 4. Effects of breed type and nongenetic factors on milk SCS, composition and yield (least square mean with standard error).

Source	N[1]	SCS (cells/mL)	Lactose (%)	Protein (%)	SNF (%)	Salt (%)	Fat (%)
Parity							
1	960	12.03 ± 0.05^{b}	4.83 ± 0.01^{a}	3.21 ± 0.01^{a}	8.76 ± 0.02^{a}	0.71 ± 0.0^{a}	2.74 ± 0.06^{a}
2	1038	12.46 ± 0.05^{a}	4.78 ± 0.01^{b}	3.18 ± 0.01^{b}	8.67 ± 0.02^{b}	0.71 ± 0.0^{b}	2.71 ± 0.05^{a}
3	696	12.57 ± 0.06^{a}	4.74 ± 0.01^{b}	3.16 ± 0.01^{b}	8.61 ± 0.02^{b}	0.70 ± 0.0^{b}	2.61 ± 0.06^{a}
≥4	575	12.63 ± 0.07^{a}	4.66 ± 0.01^{c}	3.11 ± 0.01^{c}	8.47 ± 0.03^{c}	0.69 ± 0.0^{c}	2.64 ± 0.07^{a}
Lactation stage (days in milk)							
5–60	377	12.11 ± 0.08^{b}	4.74 ± 0.02^{bc}	3.16 ± 0.01^{bc}	8.62 ± 0.03^{bc}	0.70 ± 0.00^{bc}	2.34 ± 0.09^{b}
61–180	977	12.23 ± 0.05^{b}	4.70 ± 0.01^{c}	3.13 ± 0.01^{c}	8.54 ± 0.02^{c}	0.69 ± 0.00^{c}	2.54 ± 0.05^{b}
181–305	983	12.44 ± 0.05^{a}	4.77 ± 0.01^{b}	3.17 ± 0.01^{b}	8.66 ± 0.02^{b}	0.70 ± 0.00^{b}	2.77 ± 0.05^{a}
≥306	932	12.60 ± 0.05^{a}	4.83 ± 0.01^{a}	3.21 ± 0.01^{a}	8.77 ± 0.02^{a}	0.71 ± 0.00^{a}	2.89 ± 0.06^{a}
Breed type[2]							
1	37	10.18 ± 0.26^{c}	5.12 ± 0.06^{a}	3.40 ± 0.04^{a}	9.29 ± 0.10^{a}	0.76 ± 0.01^{a}	2.74 ± 0.27^{b}
2	2949	12.43 ± 0.03^{a}	4.74 ± 0.01^{b}	3.16 ± 0.00^{c}	8.61 ± 0.01^{b}	0.70 ± 0.00^{c}	2.61 ± 0.03^{b}
3	203	12.36 ± 0.11^{a}	4.96 ± 0.02^{a}	3.30 ± 0.02^{ab}	9.01 ± 0.04^{a}	0.73 ± 0.00^{b}	2.80 ± 0.12^{b}
4	80	11.80 ± 0.18^{b}	4.98 ± 0.04^{a}	3.28 ± 0.03^{b}	9.00 ± 0.07^{a}	0.73 ± 0.01^{b}	5.03 ± 0.19^{a}
Herd size							
Small	547	12.23 ± 0.07^{b}	4.70 ± 0.02^{c}	3.13 ± 0.01^{c}	8.55 ± 0.03^{b}	0.70 ± 0.00^{b}	3.18 ± 0.07^{a}
Medium	1144	12.36 ± 0.05^{ab}	4.75 ± 0.01^{b}	3.16 ± 0.01^{b}	8.63 ± 0.02^{b}	0.70 ± 0.00^{b}	2.56 ± 0.05^{b}
Large	1578	12.46 ± 0.04^{a}	4.79 ± 0.01^{a}	3.19 ± 0.01^{a}	8.70 ± 0.02^{a}	0.71 ± 0.00^{a}	2.60 ± 0.04^{b}
Sampling season[2]							
1	1363	12.36 ± 0.04^{a}	4.77 ± 0.01^{a}	3.18 ± 0.01^{a}	8.67 ± 0.02^{a}	0.70 ± 0.00^{a}	2.77 ± 0.05^{a}
2	884	12.41 ± 0.05^{a}	4.78 ± 0.01^{a}	3.18 ± 0.01^{a}	8.67 ± 0.02^{a}	0.71 ± 0.00^{a}	2.65 ± 0.06^{a}
3	1022	12.40 ± 0.05^{a}	4.74 ± 0.01^{a}	3.16 ± 0.01^{a}	8.61 ± 0.02^{a}	0.70 ± 0.00^{a}	2.60 ± 0.05^{a}
Altitude[3]							
1	320	12.03 ± 0.09^{c}	4.85 ± 0.02^{a}	3.22 ± 0.01^{a}	8.79 ± 0.04^{a}	0.71 ± 0.00^{a}	2.86 ± 0.09^{a}
2	1736	12.33 ± 0.04^{b}	4.75 ± 0.01^{b}	3.16 ± 0.01^{b}	8.62 ± 0.02^{b}	0.70 ± 0.00^{b}	2.92 ± 0.04^{a}
3	1330	12.55 ± 0.05^{a}	4.76 ± 0.01^{b}	3.17 ± 1.01^{b}	8.65 ± 0.02^{b}	0.70 ± 0.00^{b}	2.33 ± 0.05^{b}
SCC class ($x10^3$)							
≤ 50	535	–	4.83 ± 0.01^{a}	3.22 ± 0.01^{a}	8.78 ± 0.03^{a}	0.71 ± 0.00^{a}	2.87 ± 0.07^{a}
51–200	797	–	4.84 ± 0.02^{a}	3.22 ± 0.02^{a}	8.79 ± 0.02^{a}	0.71 ± 0.00^{a}	2.75 ± 0.06^{ab}
201–350	518	–	4.80 ± 0.02^{ab}	3.20 ± 0.02^{ab}	8.72 ± 0.03^{ab}	0.71 ± 0.00^{ab}	2.68 ± 0.07^{ab}
351–500	334	–	4.74 ± 0.02^{bc}	3.16 ± 0.02^{bc}	8.61 ± 0.03^{bc}	0.70 ± 0.00^{bc}	2.45 ± 0.09^{b}
501–999	461	–	4.68 ± 0.01^{cd}	3.12 ± 0.01^{cd}	8.51 ± 0.03^{cd}	0.69 ± 0.00^{cd}	2.55 ± 0.08^{b}
≥1000	624		4.65 ± 0.01^{d}	3.09 ± 0.01^{d}	8.44 ± 0.03^{d}	0.69 ± 0.00^{d}	2.66 ± 0.07^{ab}

[1] N = Number of samples; [2] Sampling season:1 = long rainy season; 2 = dry and 3 = short rainy season; [3] Altitude 1, 1232–1600 meters; Altitude 2, 1601–2300 meters; Altitude 3, >2300 meters; [2] Breed type: (1, Local (Sheko and Fogera cattle); 2, HFC (Holstein crossbreed with different local cattle breeds); 3, BHFC (50% Boran and 50% Holstein cross); 4, Jersey;

[a,b,c,d,e,f] Means within a column with different superscripts differ significantly ($p < 0.05$); SCS (somatic cell score); Logarithmic values of SCC (somatic cell count); SNF, Solids-not-fat; MY, Milk yield.

3.4. Effects of lactation stage

The stage of lactation had a significant effect on all analysed milk parameters ($p < 0.001$), as indicated in Table 4. In the mid-lactation stage, lactose, protein, SNF and salt levels were significantly lower ($p < 0.001$) compared to the later stages of lactation. Milk yield was highest during mid-lactation, compared to the later stage. In the present study, the extended stage of lactation was associated with the highest levels of lactose, protein, SNF, salt, TS and EC, along with the lowest milk yield.

3.5. Effects of breed types

Milk from local cow breeds had significantly lower SCS, EC and milk yield ($p < 0.001$), while the fat percentage did not differ significantly between the Borana Holstein Friesian Cross (BHFC) and Holstein Friesian Cross HFC (HFC) cattle (Table 4). Jersey cattle produced milk with the highest fat and TS, while HFC cattle produced milk with the lowest levels of SNF, salt, protein, TS and lactose. No significant differences were observed in SCS or test-day milk yield between the BHFC and HFC genetic groups.

Table 4. (Continued).

Source	N	TS (%)	EC (mS/cm)	Density (kg/m^3)	Milk yield (L)
Parity					
1	960	11.49 ± 0.06^{a}	5.87 ± 0.03^{c}	1030.75 ± 0.09^{a}	10.07 ± 0.16^{b}
2	1038	11.36 ± 0.06^{ab}	6.06 ± 0.03^{b}	1030.50 ± 0.08^{ab}	10.58 ± 0.15^{ab}
3	696	11.21 ± 0.07^{b}	6.16 ± 0.04^{ab}	1030.35 ± 0.10^{b}	10.86 ± 0.19^{a}
≥4	575	11.11 ± 0.07^{b}	6.26 ± 0.04^{a}	1029.81 ± 0.11^{c}	10.36 ± 0.21^{ab}
Lactation stage (days in milk)					
5–60	377	10.96 ± 0.10^{c}	5.92 ± 0.05^{c}	1030.59 ± 0.14^{ab}	11.86 ± 0.25^{a}
61–180	977	11.07 ± 0.06^{c}	5.95 ± 0.03^{c}	1030.17 ± 0.08^{c}	12.08 ± 0.16^{a}
181–305	983	11.40 ± 0.06^{b}	6.09 ± 0.03^{b}	1030.34 ± 0.09^{bc}	9.87 ± 0.16^{b}
≥306	932	11.60 ± 0.06^{a}	6.25 ± 0.03^{a}	1030.70 ± 0.09^{a}	8.80 ± 0.16^{c}
Breed type[2]					
1	37	12.03 ± 0.31^{b}	4.93 ± 0.16^{c}	1032.78 ± 0.44^{a}	3.28 ± 0.78^{b}
2	2949	11.21 ± 0.03^{c}	6.09 ± 0.02^{a}	1030.32 ± 0.05^{b}	10.66 ± 0.09^{a}
3	203	11.80 ± 0.13^{b}	5.85 ± 0.07^{b}	1031.70 ± 0.19^{a}	10.64 ± 0.35^{a}
4	80	14.14 ± 0.21^{a}	5.84 ± 0.11^{b}	1029.66 ± 0.30^{b}	5.59 ± 0.55^{b}
Herd size					
Small	547	11.69 ± 0.08^{a}	5.83 ± 0.04^{c}	1029.61 ± 0.11^{c}	10.10 ± 0.21^{b}
Medium	1144	11.18 ± 0.06^{b}	6.16 ± 0.03^{a}	1030.42 ± 0.08^{b}	11.06 ± 0.15^{a}
Large	1578	11.30 ± 0.05^{b}	6.07 ± 0.03^{b}	1030.70 ± 0.07^{a}	10.14 ± 0.13^{b}
Sampling season[2]					
1	1363	11.42 ± 0.05^{a}	5.88 ± 0.03^{b}	1030.43 ± 0.07	11.03 ± 0.14^{a}
2	884	11.31 ± 0.07^{a}	6.23 ± 0.03^{a}	1030.54 ± 0.09	10.14 ± 0.17^{b}
3	1022	11.21 ± 0.06^{a}	6.16 ± 0.03^{a}	1030.31 ± 0.08	9.96 ± 0.16^{b}
Altitude[3]					
1	320	11.65 ± 0.11^{a}	6.02 ± 0.06^{b}	1030.82 ± 0.15^{a}	8.86 ± 0.28^{c}
2	1736	11.52 ± 0.05^{a}	5.97 ± 0.02^{b}	1030.12 ± 0.06^{b}	10.30 ± 0.12^{b}
3	1330	10.98 ± 0.05^{b}	6.19 ± 0.03^{a}	1030.73 ± 0.07^{a}	11.04 ± 0.14^{a}
SCC class (x10^3)					
≤ 50	535	11.65 ± 0.08^{a}	5.53 ± 0.04^{f}	1030.74 ± 0.11^{a}	10.72 ± 0.22^{a}
51–200	797	11.53 ± 0.07^{a}	5.73 ± 0.03^{e}	1030.88 ± 0.09^{a}	11.00 ± 0.18^{a}
201–350	518	11.38 ± 0.08^{ab}	5.92 ± 0.04^{d}	1030.61 ± 0.12^{a}	10.93 ± 0.22^{a}
351–500	334	11.03 ± 0.11^{b}	6.12 ± 0.05^{c}	1030.52 ± 0.14^{ab}	10.20 ± 0.27^{a}
501–999	461	11.05 ± 0.09^{b}	6.32 ± 0.04^{b}	1030.00 ± 0.12^{bc}	10.72 ± 0.23^{a}
≥1000	624	11.09 ± 0.08^{b}	6.82 ± 0.04^{a}	1029.66 ± 0.11^{c}	9.07 ± 0.20^{b}

[1]N = Number of samples; [2]Sampling season:1= long rainy season; 2= dry and 3= short rainy season; [3]Altitude 1, 1232–1600 m; Altitude 2, 1601–2300 m; Altitude 3, >2300 m; [2]Breed type: (1, Local (Sheko and Fogera cattle); 2, HFC (Holstein crossbreed with different local cattle breeds); 3, BHFC (50% Boran and 50% Holstein cross); 4, Jersey;

[a,b,c,d,e,f]Means within a column with different superscripts differ significantly ($P < 0.05$); SCS (somatic cell score), Logarithmic values of SCC (somatic cell count); SNF, Solids-not-fat; Milk yield in litre; EC, Electrical conductivity in millisiemens per centimeter (mS/cm); TS, Total solids.

3.6. Effects of herd size and season

Milk SCS, composition and yield were significantly affected by herd size ($p < 0.01$) (Table 4). Larger herds had significantly higher SCS, lactose, protein, salt, SNF and density ($p < 0.01$) compared to smaller herds. In small-scale farms, milk had the highest fat and TS contents, along with the lowest EC. The highest milk yield was observed in medium-scale farms ($p < 0.01$), though SCS did not differ significantly between small and large herds. The sampling season did not significantly impact most milk components ($p > 0.05$), except for EC and milk yield. During the long rainy season (June to September), the highest milk yield and lowest EC were recorded ($p < 0.001$).

3.7. Effects of altitude

Altitude variation had a significant impact on all tested milk traits ($p < 0.01$), as shown in Table 4. Cows at low altitudes (1232–1600 m) produced milk with the highest lactose, protein, SNF and salt contents, along with the lowest SCS and milk yield. In contrast, cows at high altitudes (>2300 m) had significantly higher SCS, EC and milk yield, but lower fat and TS ($P < 0.01$). The highest fat percentage was found at low and mid-altitudes (1601–2300 m).

3.8. Effects of SCC class

All analysed milk compositions and yields traits were significantly affected by SCC class ($p < 0.01$) (Table 4). Among the milk samples, 40.75% fell within the SCC class of ≤ 200 x 10^3 cells/mL. No significant difference in milk yield and composition was found between SCC classes of ≤ 200x10^3 up to 350 x10^3 cells/mL, or between 250x10^3 and 500x10^3 cells/mL, except for EC. As the SCC increased, EC content in the milk also rose.

4. Discussion

In this study, high milk SCC was recorded, indicating a significant prevalence of mastitis in Ethiopia, consistent with previous reports showing rates of 43.6% (Girma & Tamir, 2022) and 47.0% (Getaneh & Gebremedhin, 2017). Similarly, milk contaminated with bacteria had higher SCC compared to healthy milk (Hisira et al., 2023). Supporting our findings, other studies have also highlighted poor milk quality on Ethiopia dairy farms, with 90% of raw milk analysed falling to meet the microbial quality standards (Berhanu et al., 2021). The milk composition results from our study indicate that the fat percentage was notably low, falling below 3.25% for the East African community (EAC) (EAC, 2018) and 3.34% for the Ethiopian standard (ES) (ES, 2012). These figures are lower than the 3.7% fat content reported by Kebede (2018). Similarly, Zebib et al. (2023) reported raw milk fat content ranging from 2.17% to 3.17% in Ethiopia. Zahumenská et al. (2024) also recorded a low fat percentage of 2.84. According to Zebib et al. (2023), 80% of the milk analysed in Ethiopia had fat content below the ES. In Gambia, a study by Olaniyan et al. (2023) revealed significantly variability in fat percentage, ranging from 1.21% to 14.04%. The low-fat content observed in our study may be attributed to the milk sampling methods used, which is one of the study's limitations. Milk composition is influenced by milking systems and can vary throughout the milking process (Hurtaud et al., 2020; Zahumenská et al., 2024). Among milk components, fat is the most variable component during milking (Vangroenweghe et al., 2002). Unlike other milk traits, fat content is particularly affected by the milk sampling fraction, with higher fat percentage typically found in residual milk (Aranguiz et al., 2019; Hurtaud et al., 2020). Furthermore, the variability and low-fat content could be partially related to breed differences and the feed ration used on dairy farms. Most farms in the study areas use brewery by-products as animal feed, which may reduce fat synthesis in mammary glands of dairy cows (Aranguiz et al., 2019; Rivero & Anrique, 2015; Terefe et al., 2023).

The protein, SNF and lactose contents observed in the present study were within the range of the Ethiopian Standard (ES) (ES, 2012). However, the SNF content was lower than the EAC standard of 8.5% (EAC, 2018). Zebib et al. (2023) reported that 80.2% of the protein and SNF in raw milk was below the ES, whereas our results aligned with the Ethiopian standard. Similarly, SNF (8.48), lactose (4.64), and protein (3.14) level have been reported for the Holstein Frisia cattle breed in Ethiopia (Kebede, 2018). In contrast to our findings, Kebede (2018) reported a higher values of 12.16% for total solids.

The average test day milk yield in our study was lower than the 11.7 litres/day reported in central Ethiopia (Lobago et al., 2007), 14.7 litres/day in Hawassa City (Abebe et al., 2023), and 15.8 litres/day in central Rift Valley (Tolla et al., 2006) for crossbred dairy cattle under farmer management conditions. However, our result was higher than the 5.98 ± 1.01 litres/day (Duguma, 2022), 6.77 ± 1.09 litres/day (Yoseph et al., 2022) and 8.4 litres/day (Ndambi et al., 2017) reported in other parts of Ethiopia. The observed variation in milk yield and composition can be attributed to disparities between the genetic potential and environmental factors such as feeding, climatic condition, housing and health care, with many cows being subjected to suboptimal management condition.

Our results demonstrated that milk component traits such as lactose, protein, SNF, salt, density, total solids, fat and milk yield were negatively and significantly associated with SCS. SCS widely recognized as a reliable indicator of udder health. This is in agreement with the previous research showing that the higher SCS adversely affect both milk production and quality (Cinar et al., 2015; El-Tahawy & El-Far, 2010; Franzoi et al., 2020). In line with the finding of Boas et al. (2017), milk electrical conductivity was positively associated with SCS (0.41). The EC of milk increases significantly when cows are experiencing clinical mastitis (Juozaitienė et al., 2015; Norberg, 2005), likely due to the release of sodium (Na) and potassium (K) ions into milk from blood vessels (Ontsouka et al., 2003). Consequently, milk electrical conductivity can serve as an effective method for selection against mastitis in cows, in conjugation with SCS (Norberg et al., 2004). Our results align with those of Antanaitis et al. (2021), who reported a negative correlation between lactose percentage and SCS. Similar to the current results, other studies have suggested that lactose should be used alongside SCS and EC as an indicator of subclinical mastitis (Antanaitis et al., 2021; Ebrahimie et al., 2018). However, contrary to findings of other authors (da Silva et al., 2018; Miglior et al., 2007), we found negative correlation close to zero between milk yield and lactose percentage, although this was not statistically significant. This discrepancy may be attributed to negative energy balance in the diets of the dairy cattle and underlying udder health issues (Hamon et al., 2024). Supporting our findings, an earlier study by Welper and Freeman (1992) reported a negatively correlation between lactose percentage and milk yield (_0.08). Additionally, a genetic correlation of _0.02 between milk yield and lactose percentage was reported by Costa et al. (2019). A stronger positive correlation among protein, SNF, lactose and salt observed in this study was in agreement with Olaniyan et al. (2023).

Breeds and genetic groups are known to influence both milk composition and yield (Magro et al., 2023; Manuelian et al., 2018). Several studies in Ethiopia have shown that breed and genetic background significantly affect milk traits (Kebede, 2018; Mesfin & Getachew, 2007; Yoseph et al., 2022). In our study, the highest fat percentage and total solids were observed in the Jersey cattle breed, consistent with the findings of Yoseph et al. (2022). The HFC and BHFC genetic groups produced milk with the highest SCS, likely due to the selective breeding of Holstein Friesian cows for higher milk production, which increases their susceptibility to mastitis (Curone et al., 2018). In contrast, the low-producing indigenous cattle had the lowest SCC and are known shown for their resistance to various diseases. Differences in milk SCC and composition across cattle breeds were evident in our study, in contrary to the findings of Cheruiyot et al. (2018) in Tanzania. Besides, milk sampled from cattle with unknown admixture levels of exotic genes could have influenced the SCS, composition and yield. Previous studies indicated that Ethiopian crossbred animals had an average of 72% exotic dairy genetics proportion (Gebrehiwot et al., 2020). The extent to which the SCS is affected by different admixture levels requires further investigation.

SCS and milk composition traits (lactose, protein, SNF, salt and TS) increased significantly with advancing days in milk, while milk yield decreased. As days in milk progress leads to higher SCC (Sebastino et al., 2020). High SCC has been reported to negatively affect feed efficiency (Potter et al., 2018) and conception rates in dairy cows (Rearte et al., 2022). In the study area, farmers milked cows beyond the recommended 305 days, with extended lactation observed in 28% of the sampled lactating cows. This extended lactation may be also linked to repeat breeding (Eshete et al., 2023), potentially compromising milk quality and quantity.

The lowest SCS was recorded in cows in the first parity. In line to our study, with increasing parity being associated with higher SCS (Sabek et al., 2021; Sebastino et al., 2020). The prevalence of mastitis tends to increase with parity (Alemu et al., 2013). In contrast to our findings, Tolla et al. (2006) reported that milk yield and milk composition of Holstein-Friesian cows in the central rift valley of Ethiopia were not affected by parity. In cows with parity of 4 and above, milk lactose, protein, SNF, salt and density were observably reduced in the studied population. In agreement with a previous study, a greater lactose percentage was recorded in first- than later-parity Holstein cows in Italy (Costa et al., 2019)

In the current study, we found no significant differences in milk composition and yield, except EC between the SCC classes of ≤50 and ≤200×10^3 cells/mL. Similarly, no significant difference in milk composition and test-day milk yield were observed between the SCC class of ≤200×10^3 and up to 350×10^3 cells/mL, aside from EC. At SCC up to $500 \text{x} 10^3$ cells/mL, there were no significant differences in lactose, protein, SNF, salt, TS and density. However, milk yield and composition were significantly impacted in the SCC class of >500×10^3 cells/mL. Similar results were reported that an increase of SCC impairs milk productivity, profitability and quality (Franzoi et al., 2020). In contrast, a study conducted in Brazil (Botaro et al., 2015) and Tukey (Cinar et al., 2015) found that milk fat is unaffected by SCC. Various SCC thresholds have been recommended based on climatic conditions, breeds and production systems. For instance, an SCC of 310×10^3 cells/mL was proposed to distinguish healthy cow from those subclinical mastitis in India (Jadhav et al., 2018), while 546×10^3 cells/mL was suggested for small-scale dairy farms in Kenya (Ogola et al., 2007). In tropical countries, the standard SCC limit is set at ≤ $350 \text{x} 10^3$ cells/mL, whereas in East Africa ≤ 300 $\text{x} 10^3$ cells/mL (EAC, 2018). However, some authors suggested a lower SCC cut-off of 100×10^3 cells/mL (Sumon et al., 2020; Zhang et al., 2022). Moreover, combining SCC with differential somatic cell count (DSCC) (Bobbo et al., 2020) or incorporating SCC measurement with bacterial culture and clinical detection (Kurz et al., 2019) has been proposed as a more accurate method for assessing udder health.

Large-scale commercial farms had higher SCC levels, while in small-scale farms, milk with high fat, high TS, low EC and low density was recorded. The highest milk yield was found in medium-scale farms, but the level of SCS was not significantly different from that of the larger farms. The reason for such variation might be due to the management of dairy farms not being in accordance with cattle population, inadequate provision of balanced rations and breed of cattle found in the farms. A previous report also indicated that the highest milk loss was observed in large-scale farms due to subclinical mastitis in Ethiopia (Tesfaye et al., 2010). A study conducted in Thailand revealed that the highest daily milk and milk fat in small farms were higher than those in medium and large farms (Rhone et al., 2008).

The highest test-day milk yield and lowest EC were recorded during the long rainy season. A similar finding was reported by Bedada et al. (2021), who reported that the daily milk yield was higher in the rainy season than in the dry season. The variation in milk yield may be due to the availability of feed, crop residues and supplemental feed. The temperature also affects the conductivity because ions move faster at higher temperatures, thereby increasing the conductivity. The reason for most milk traits not being affected by sampling season might be because dairy cattle were kept confined for a longer time for all seasons and had insufficient longitudinal data.

Altitude has a significant influence on milk composition, yield and SCS, as reported by Alrhmoun et al. (2024) and Qian et al. (2024). Herds located at altitudes below 1600 m had the lowest SCS and milk yield. This is consistent with Bedada et al. (2021), who reported the lowest milk yield in the lowlands of the Southern Ethiopian Rift Valley. In contrast, Qian et al. (2024) found that as altitude increased from sea level to1600 m, 2700 m and 3800 m, daily milk production decreased, but protein, fat, lactose, ash and total solid contents in raw milk were higher at higher altitudes. Similarly, a study across altitudes ranging from 600–900 m, 901–1200 m, and 1201–1500 m revealed that farms situated above 1200 m had higher fat, protein, urea and somatic cell content, while lactose content was lower (Alrhmoun et al., 2024). At extreme altitudes, environmental factors such as radiation, temperature, moisture and humidity impact cows' metabolic activity. For instance, at altitude of 3600 m compared with 1600 m in the Tibetan Plateau, nutrient digestibility was lower, rumen fermentation was impaired and cows' basal metabolism rate increased (Qiao et al., 2013). These physiological and environmental changes can significantly influence milk composition and yield.

5. Conclusions

In conclusion, the highest SCS was recorded in this study. An increase in SCS negatively affects both milk yield and composition. In addition, breed and non-genetic factors influenced most of the traits examined. Thus, factors such as breed type, lactation stage, altitude, and herd management should be considered when selecting cattle to reduce SCC, improved milk yield and enhance milk quality. Further research is recommended, incorporating larger dataset with repeated records.

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Authors' contributions

TFC, SM, GMT, OM, RM, EN and TST: Conceptualization, methodology; TFC: investigation, formal analysis; Writing – original draft; TFC, GMT, RM,ZE and SM: validation, software; SM, OM, AT, GG: resources, Project administration; TFC, SM, GMT, OM, RM, EN, TST,AT; ChED, GG, ZE: writing—review and editing; SM, GMT, OM, RM, EN, TST,AT; ChED, GG, ZE: supervision; SM, OM and AT: funding acquisition; TFC,SM, GMT, RM, EN, ZE: data curation, visualization. All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

Disclosure statement

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About the authors

Tegegn Fantahun Chernet is currently a PhD candidate in Biotechnology at Addis Ababa University, Ethiopia. Since 2018, he has served as a researcher at the Bio and Emerging Technology Institute in Addis Ababa. Previously, he was a Lecturer at Mizan-Tepi University (2009–2018) and a Junior Instructor at the Mizan Agricultural Technical, Vocational, and Educational Training College (2007–2009). Tegegn holds a master's degree in animal Genetics and Breeding from Bahir Dar University and a bachelor's degree in animal production and health from Jimma University, providing a solid foundation for his research and academic career. His research interests focus on advancing genetic and genomic evaluation in livestock, exploring udder genetics in dairy cattle, milk and dairy products, reproductive biotechnology in animals, and studying the effects of heat stress and greenhouse gas emissions on livestock productivity.

Dr. Okeyo Mwai holds MSc Animal Science (Animal Genetics) from University of California, Davis and a PhD in Animal Breeding and Genetics from University of Nairobi. Ally Okeyo Mwai was the Program Lead of ILRI's Global Livestock Genetics- Live Gene Research Program. Okeyo is a quantitative geneticist with over 30 years of experience in practical design and implementation of livestock improvement programs in sub-Saharan Africa and South Asia regions.

Dr. Selam Meseret, currently serving as the Program Coordinator for the African-Asian Dairy Genetic Gains and Enviro-cow Projects at the International Livestock Research Institute in Addis Ababa, Ethiopia, holds a Ph.D. in Animal Production from Addis Ababa University, Ethiopia. Her research focuses on livestock quantitative genetics and genomics, where she has made significant contributions through strategic partnerships and training initiatives in genetic evaluation. Her rigorous research and leadership have significantly influenced the implementation of effective genomic evaluation and big data approaches within national dairy cattle performance recording systems, substantially contributing to the genetic improvement initiatives in Ethiopia.

Dr. Enyew Negussie (PhD): is livestock geneticist and senior scientist at the Natural Resources Institute (Luke) Finland and adjunct Professor at the University of Helsinki. He has over 25 years' experience in livestock breeding programs, genomics, animal evaluation, and sustainable dairy development. He has led and participated in several national and international livestock development projects in Africa and Europe. Dr Enyew supervised several MSc. and PhD students and published more than 160 scientific publications, the majority of which on peer reviewed scientific journals.

Professor Raphael Mrode is Professor of Quantitative Genetics and Genomics at Scotland's Rural College. He obtained his PhD from Edinburgh University on Animal Genetics and Breeding. Raphael Mrode is principal scientist in Quantitative Dairy Cattle genetics at the International Livestock Research. His research interests include data modelling and analysis, the incorporation of molecular information in genetic evaluation procedures, the application of innovative approaches for data capture, analysis and feedback and investigating methods for generating alternative and novel phenotypes in small dairy systems in developing countries.

Dr. Getinet Mekuriaw Tarekegn (PhD in Applied Genetics) is a Geneticist and Bioinformatician currently works for the Scotland's Rural College (SRUC, based at Roslin Institute Building, University of Edinburgh, Edinburgh, United Kingdom (UK). He is also an Adjunct Professor of Genomics and Bioinformatics at Addis Ababa University, Ethiopia. As a researcher he works on routine genetic and genomic evaluation of beef breeds, crossbreeds and multi-breed genetic and genomic evaluation in the UK and abroad; developing new methods and approaches like Blending (the integration) of International Genetic evaluation results to the national proofs in UK; Establishing a genetic and genomic evaluation pipeline for the Global South. He is also involved in: i) the de-novo assembly of the African cattle genome project; ii) Multi-country, multi-breed (cattle breeds) and multi-trait genetic evaluation project which is on-going in four countries in Europe. Moreover, he is as associate editor for Genome Journal, Canadian Science Publishing.

Dr. Zewdu Edea (PhD) is a senior researcher of Animal Genomics at the Bio and Emerging Technology Institute. He received his PhD from Chungbuk National University (CBNU) of South Korea. He has more than 15 years of research and teaching experience. He authored and co-authored over 20 papers. His research focuses on uncovering the genomic diversity and adaptation of ruminant livestock species to extreme environments.

Dr. Gebregziabher Gebreyohanes holds a PhD in Dairy Animal Breeding from Kasetsart University, Thailand, and both a BSc and MSc from Haramaya University, Ethiopia. Currently a Senior Scientist at the International Livestock Research Institute, he has served in multiple leadership roles and brings over 25 years of research experience, with deep expertise in the livestock sector.

Dr. Chinyere Ekine-Dzivenu holds a Ph.D. from the University of Alberta, Canada and works as a scientist and statistical geneticist at the International Livestock Research Institute (ILRI) in Nairobi, Kenya. Dr. Ekine-Dzivenu is passionate about advancing livestock genetic improvement in small holder farming systems through genomics and advanced animal genetics and breeding strategies. Her present research is centered on investigating the effects of climate change and heat stress on livestock production in smallholder systems, alongside efforts to enhance feed efficiency and lower methane emissions. Dr. Ekine-Dzivenu finds deep fulfillment in giving back and is committed to lifelong learning.

Dr. Asrat Tera, PhD in Animal Breeding and Genetics, holds an MSc in Animal Production and a BSc in Animal Production and Range Sciences from Hawassa University, Ethiopia. He currently serves as the Director General of the National Animal Genetic Improvement Institute in Ethiopia.

Professor Tesfaye Sisay Tessema is a Professor in Health Biotechnology at the Institute of Biotechnology, Addis Ababa University. Holds a PhD in Immunology from the Johannes Gutenberg University of Mainz, Institute of Medical Microbiology and Hygiene, Germany; an MSc in Molecular Biology from the Interuniversity Program in Molecular Biology, Catholic University of Leuven and Free University of Brussels, Belgium; and a Doctor of Veterinary Medicine (D.V.M.) from Addis Ababa University. Research interests encompass Immunology, Microbiology, and Molecular Biology, with current projects focusing on developing immunodiagnostic assays for diarrheal pathogens, exploring the molecular diversity of zoonotic pathogens, and investigating antimicrobial resistance within a One Health framework. Experienced in project management and leadership, with a strong track record of mentoring MSc and PhD students.

ORCID

Tegegn Fantahun Chernet http://orcid.org/0000-0001-9966-4437
Okeyo Mwai http://orcid.org/0000-0003-2379-7801
Selam Meseret http://orcid.org/0000-0002-1178-1821
Enyew Negussie http://orcid.org/0000-0003-4892-9938
Raphael Mrode http://orcid.org/0000-0003-1964-5653
Getinet Mekuriaw Tarekegn http://orcid.org/0000-0001-7221-2473
Zewdu Edea http://orcid.org/0000-0003-2343-4832
Gebregziabher Gebreyohanes http://orcid.org/0009-0001-5042-2848
Chinyere Ekine-Dzivenu http://orcid.org/0000-0002-8526-435X
Tesfaye Sisay Tessema http://orcid.org/0000-0002-4103-5029

Data availability statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

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