High yield dairy cattle breeds improve farmer incomes, curtail greenhouse gas emissions and reduce dairy import dependency in Tanzania

James W. Hawkins*[1,2]
Adam M. Komarek[3]
Esther M. Kihoro[4]
Charles F. Nicholson[5]
Amos O. Omore[4]
Gabriel U. Yesuf[1,6]
Polly J. Ericksen[4]
George C. Schoneveld[2]
Mariana C. Rufino[1]

[1] Lancaster Environment Centre, Lancaster University, Lancaster, UK
[2] Center for International Forestry Research (CIFOR), Nairobi, Kenya.
[3] School of Agriculture and Food Sciences, University of Queensland, Queensland, Australia
[4] International Livestock Research Institute (ILRI), Nairobi, Kenya
[5] Department of Agricultural & Applied Economics, University of Wisconsin-Madison, Madison, USA
[6] Department of Geography & Environmental Science, University of Reading, Reading, UK (current address)

*Corresponding author. Email address: jameshawkins702@gmail.com

Abstract

Tanzania's dairy sector is poorly developed, creating reliance on imports for processed, value-added dairy products and threatening food security, particularly when supply chains are disrupted due to market volatility or armed conflicts. The Tanzanian Dairy Development Roadmap (DDR) is a domestic development initiative that aims to achieve dairy self-sufficiency by 2030. Here, we model different outcomes of the DDR, finding that adoption of high yield cattle breeds is essential for reducing dairy import dependency. Avoided land use change resulting from fewer, higher yielding dairy cattle would lead to lower greenhouse gas (GHG) emissions. Dairy producers' average incomes could increase despite capital expenditure and land allocation required for the adoption of high yield breeds. Our findings demonstrate the importance of bottom-up development policies for sustainable food system transformations, which also support food sovereignty, increase incomes for smallholder farmers and contribute towards Tanzania's commitments to reduce GHG emissions.

Introduction

East Africa has the highest density of dairy cattle in sub-Saharan African (SSA), contributing ~23% to national agricultural GDP[1,2]. Agricultural productivity growth on smallholder farms has stalled in recent years[3,4], yet productivity gains in crop and livestock supply chains are crucial to meet food demand whilst reducing greenhouse gas (GHG) emissions[5,6,7]. Tanzania has the second largest herd in East Africa with 28 Million cattle (second to Ethiopia's herd of 70 Million)[8], but the dairy sector is poorly developed. On farms, a combination of low yielding breeds, feeds with low nutritional value, and low uptake of health and reproductive services limits productivity and results in low and highly seasonal surpluses[9]. Within the dairy value chain, poor handling and improper refrigeration results in frequent contamination and spoilage[10]. Whilst these factors are common in Africa, in Tanzania milk quality and safety issues are major barriers to the development of dairy value chains[9,10], creating reliance on imports for processed, value-added dairy products equal to a net trade deficit of 23 Million USD in 2020[11].

The 'Dairy Development Roadmap' (DDR) was conceived in 2016 as part of a broader Livestock Master Plan to reduce import-dependency by improving dairy productivity, allowing more cost-competitive domestic production to substitute for imports[12]. Changing cattle genetics is a prominent feature of the DDR's strategy, due to the low yield potential of local *Bos indicus* cattle – the prevalent milk producing breeds in Tanzania. Promoting higher-than-historical adoption rates of improved *Bos taurus x Bos indicus* crosses, was deemed essential for reducing dependency. In an accompanying feasibility study, the Tanzanian Livestock Sector Analysis (TLSA) projected that adoption rates leading to up to 60% improved cattle in regions with good agroecological potential would enable Tanzania to reach dairy self-sufficiency by 2030, whilst increasing income among households that adopt improved breeds[13]. Consultations with sector stakeholders confirmed genetic gains rank high among alternative interventions to increase production and promote development, indicating the validity of the DDR goals for dairy farmers and key stakeholders[14]. Breeds with high feed conversion efficiency produce milk with up to 35% lower GHG emissions intensity, implying

Tanzania's genetic improvement goals could reduce the dairy sector's carbon footprint[15]. Previous assessments have been limited in scope neglecting the risks of land use change and did not account for the costs and benefits from breed adoption[16,17].

This study evaluates the potential of the DDR to deliver multiple development ambitions in Tanzania's dairy sector whilst reducing GHG emissions. The desired outcomes are to achieve self-sufficiency by 2030 by increasing milk production to eliminate import dependency, and improving welfare of dairy producers through higher income. Simulations are conducted for the 2018 to 2030 period using a simulation model and empirical data from a comprehensive household survey[18]. Productivity and changes in incomes are compared against GHG outcomes and Tanzania's NDC mitigation pledge, which targets a 30-35% reduction in emissions from 'Business as usual' by 2030[19]. Four scenarios are evaluated which represent plausible representation of the DDR, differing only in milk production targets, and the adoption of improved cattle among households. Production targets are aligned with the DDR projected production levels required to eliminate import dependence, involving between 150-230% growth over the base year production level across regions (see Methods). Scenarios are conducted for four districts with highest agroecological potential, three in the southern highlands and one in Tanzania's coastal region. The *Baseline* and four DDR scenarios are described here (additional details in Methods):

Baseline represents the 'Business as usual' scenario with minimal technology or policy interventions. Milk production grows because of larger dairy cattle numbers rather than increased productivity. Dairy households further maintain the same cattle breeds as those observed in the 2018 base year. The *Baseline* thus reflects a 'no policy' scenario as in the dairy development roadmap[12]. ***Meagre*** offers better diets for improved and local cattle with a greater provision of forages and concentrate feeds which raise milk yields by 90-180%. However, few households not already owning improved cattle adopt (<3%), and breed distribution per district remain the same as 2018. Milk production equal to 70% of the 2030 targets are simulated, ensuring the feasibility of realizing production targets under this scenario. Since breed distributions remain constant, production targets are achieved through higher yields per cow and a larger dairy herd size. ***Middle road*** increases milk yield through better feeding as in *Meagre*. A higher proportion (10-13%) of dairy households newly adopt improved breeds, leading to 50% realisation of the breed targets of the Tanzanian Livestock Sector Analysis. Due to more productive improved cattle, the dairy herd increases less than under *Meagre*, yet fulfilling 70% of milk production targets. ***High ambition*** increases milk yield through better feeding. The breed targets of 60 and 27% improved cattle for highlands and coastal districts are realised, with higher household adoption rates (18-23%). Due to the high percentage of improved cattle in the herd, herd size is the smallest among scenarios and fulfils 70% of the 2030 milk production targets. ***High ambition ++*** increases milk yield through better feeding. However, this scenario differs from all other scenarios by meeting 100% of the production target to minimise dependency. This happens with high adoption rates of improved breeds.

For each scenario, household income is calculated on the basis of changes in herd size and breeds and feeding practices for three representative dairy household types: (i*) Local-only*, who are households owning only local cattle in the base year of 2018 and who do not adopt improved cattle, (ii*) New-improved*, households who adopt improved cattle for the first time in 2018, replacing local cattle herds, and (iii) *Extant-improved*, households who already owned improved cattle in 2018 and maintain improved breeds throughout the 12-year simulation period.

Results

Increasing milk production and reducing carbon footprints

The adoption of improved feeding practices led to higher total feed intake and more nutritious diets for local and improved cows under all scenarios (see SI Table S5). The improved diets increased milk yields for local cattle by as much as 179% to an average of 736±132 (±s.d) kg fat-and-protein corrected milk (FPCM) yr^{-1} in the highland districts, and up to 141% to an average of 701±126 kg FPCM yr^{-1} in the coastal district of Mvomero (Extended Data Table 1). For improved cattle, milk yields increased by up to 137% in highlands districts to a region-wide average of 2,861±544 kg FPCM yr^{-1} (+93%). In Mvomero they increased to a district average of

2,414±459 kg FPCM yr^{-1} (+135%). Changes in feeds and breeds allowed achieving production targets with small to moderate reductions in herd sizes relative to the *Baseline* (Extended data Table 1) compared to the historically extrapolated herd population growth under *Baseline*. Under *Meagre* where breed compositions remained the same as the base year, improved feeding allowed meeting production targets with a 18% reduction in the dairy herd size. Under scenarios *Middle road* and *High ambition*, the proportion of improved cattle in the herd increases by 22.1 and 45.7% respectively, relative to *Baseline*. The higher productivity of improved and local breeds however results in a reduction in animal numbers of both cattle breeds; 35.8% for local and 10.0% for improved under *Middle road*, and 52.0% and 5.0%, for local and improved respectively, under *High ambition*. Under *High ambition* ++ the quantity of improved cattle increases in absolute terms by 20.5% over *Baseline*, while the local cattle herd declines by 40.0%. The increase in improved cattle in the herd however allows the production target to be met with herd size declines by 17.5% relative to *Baseline*. The results therefore indicate that production targets could be realised with absolute reductions in herd sizes, if these occur as a result of 80 and 90% average increases in yields of improved and local cows respectively, and combined with moderate (+20.5%) increases in the population of improved cattle.

The *Baseline* GHG emission intensity was 9.6±1.6 kg CO_2eq kg^{-1} FPCM (Fig 1a). Most of the carbon footprint was associated with crop and grassland expansion to feed the dairy herd accounting for 61.0%±10.2 of the carbon emissions. Direct sources including enteric fermentation, manure, crop and grassland soils, and fossil energy use accounted for the rest (39.0%±6.5%). Details on GHG emissions and emissions intensities, excluding land use change, and disaggregated by breed are provided in Extended Data Fig. 1. Estimates of enteric CH_4, which comprises over 95% of direct GHG emissions in East African dairy, are consistent with recent experiment and model-based studies[20]. In the highlands of Kenya, dairy cows were reported to produce 34.1 kg CH_4 yr^{-1} [21]. By comparison, this study estimated values of 45.5 kg CH_4 yr^{-1}, 33% higher than the Kenyan values, which relates to higher feed digestibility, >60% in Kenya compared to 45-55% for the current study[21]. Other

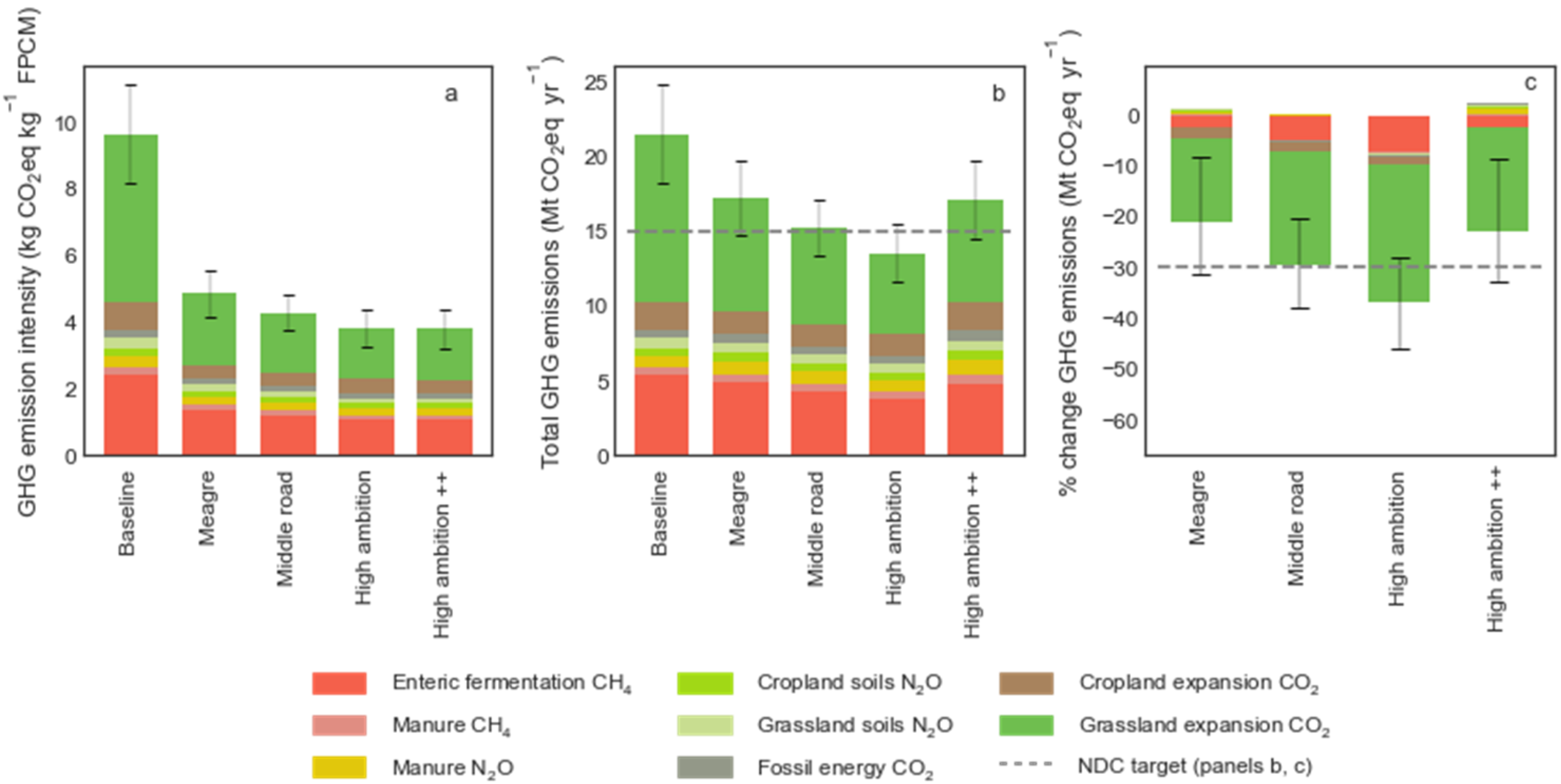

Figure 1: Greenhouse gas emissions from different scenarios: *Baseline*, *Meagre*, *Middle road, High ambition,* and *High ambition ++.* (a) Emissions intensities expressed in kg CO_{2eq} per kg of fat and protein corrected milk (FPCM), (b) Absolute emissions for the simulated region expressed in Megatonnes of CO_{2eq} (1Mt = 10^6 tonnes), (c) Percent change in absolute emissions relative to *Baseline* scenario. Error bars indicate 95% confidence interval based on uncertainty analysis (see Methods) expressed in relation to the total GHG estimate (panels a,b) and net GHG change relative to *Baseline* (panel c). Dotted lines on panels b and c indicate targeted reduction level of Tanzania's Nationally Determined Contribution which is defined as a 30% reduction from *Baseline*. FPCM = fat- and protein-corrected milk.

studies[22] with zebu cattle fed Rhodes grass in Kenya showed estimated 48.7 kg CH_4 yr^{-1} similar to this study of 46.7 kg CH_4 yr^{-1}. Our emission intensity estimates for improved cattle were 2.0±0.3 kg CO_2eq kg^{-1} FPCM which are consistent with those estimated by FAO ranging from 1.9-2.2 kg CO_2eq kg $FPCM^{-1}$ excluding LUC emissions[23]. Local cattle emissions intensities were estimated as 9.6±1.0 kg CO_2eq kg^{-1} FPCM, 53-66% lower than the national average estimates by FAO of 20.3-28.8 kg CO_2eq kg^{-1} FPCM[23]. These higher intensities by FAO result from the high proportion of cattle raised in the less productive arid and pastoral production systems. Moreover, herds in our study region which were based on the household survey (see Methods) have a higher proportion of productive cattle than the national average, diluting the 'maintenance' emissions of the herd[23]. Our estimates of GHG emissions from LUC at 61% of the dairy carbon footprint correspond well with the 48-62% estimates by the GLOBIOM model for dairy in sub-Saharan Africa[24,25].

Scenario *Meagre* reduced emissions intensity by 50.0±6.6% to 4.9±0.7 kg CO_2eq kg^{-1} FPCM due to higher milk yields and reductions in dairy land use (Extended Data Fig. 2). Scenarios *Middle road* and *High ambition* resulted in reductions in emission intensity by 55.5±7.2% to 4.3 ± 0.6 kg CO_2eq kg^{-1} FPCM and by 60.4±9.1% to 3.8±0.6 kg CO_2eq kg^{-1} FPCM, respectively. Scenario *High ambition ++* similarly resulted in a reduction in emissions intensity by 60.5±8.8% to 3.8±0.6 kg CO_2eq kg^{-1} FPCM. The roadmap scenarios resulted in absolute reductions in emissions from *Baseline* (Fig. 1b,c) in the amount of 20.0% for *Meagre*, 29.2% for *Middle road*, 37.0% for *High ambition*, and 20.6% for *High ambition ++.* While all scenarios reduced GHG emissions relative to *Baseline*, only under scenario *High ambition* (full realization of the DDR genetics targets) would these be consistent with Tanzania's NDC target (30-35%) (Fig. 1c). Further analysis of the likelihood of meeting the target under this scenario suggests a high likelihood, with only a 6.8% probability of not fulfilling the minimum 30% reduction level.

Improving dairy household income

The roadmap scenarios resulted in positive aggregate effects on income, which was a result of increases in dairy revenue driven by improved milk yields per cow. These income gains occurred in spite of capital expenditure and land allocation associated with adopting improved cattle and changing feeding practices (see Methods), and despite small declines in herd sizes under some scenarios. Herd sizes (Fig. 2a) for *Local-only* households increased the highest under *Meagre* (4 head), followed by *High ambition* ++ (3 head), and *Middle road* (2 head). *High ambition* leads to the smallest herd size increase and the smallest quantity of local cattle with a decline of 1 head. Herd sizes for *Extant-improved* households who maintain improved cattle were small for the *Baseline* (mean = 3 head) and increased little (0 to 1 head) across scenarios. For *New-improved* households, herd sizes decreased by 6 to 8 head across scenarios. As these households substituted herds of local for improved cattle, higher milk production increased income by between 98 (*Middle road*) to 157 USD capita^{-1} yr^{-1} (*High ambition*). For *Local-only* households, increases in income were highest under *Meagre* (+135 USD capita^{-1} yr^{-1}), followed by *Middle road* (+117 USD capita^{-1} yr^{-1}), *High ambition* ++ (+119 USD capita^{-1} yr^{-1}), and *High ambition* (+71 USD capita^{-1} yr^{-1}). These small changes under the latter scenarios were because of smaller herd sizes (Fig. 3a) resulting in less income from milk. For *New-improved* households, income increased across all scenarios, ranging from 102 USD capita^{-1} yr^{-1} under *High ambition* to 214 USD capita^{-1} yr^{-1} under *High ambition* ++ (Fig. 3a).

Considering the varying numbers of dairy household types across the districts, the average change in herd size, weighted by each household's proportion within the population, indicated that the roadmap scenarios would have only small changes (Fig. 2b). As the average for all dairy households, the roadmap scenarios resulted in herd size changes ranging from small declines under *High ambition* to increases of up to 2 head per household under *Meagre*. Associated with these changes (Fig. 3b), average changes in income, expressed in relation to *Baseline* dairy income, were +86% (+82 USD capita yr^{-1}) (*High ambition*), +106% (102 USD capita yr^{-1}) (*Middle road*), +110% (105 USD capita yr^{-1}) (*Meagre*), and +147% (140 USD capita yr^{-1}) (*High ambition* ++).

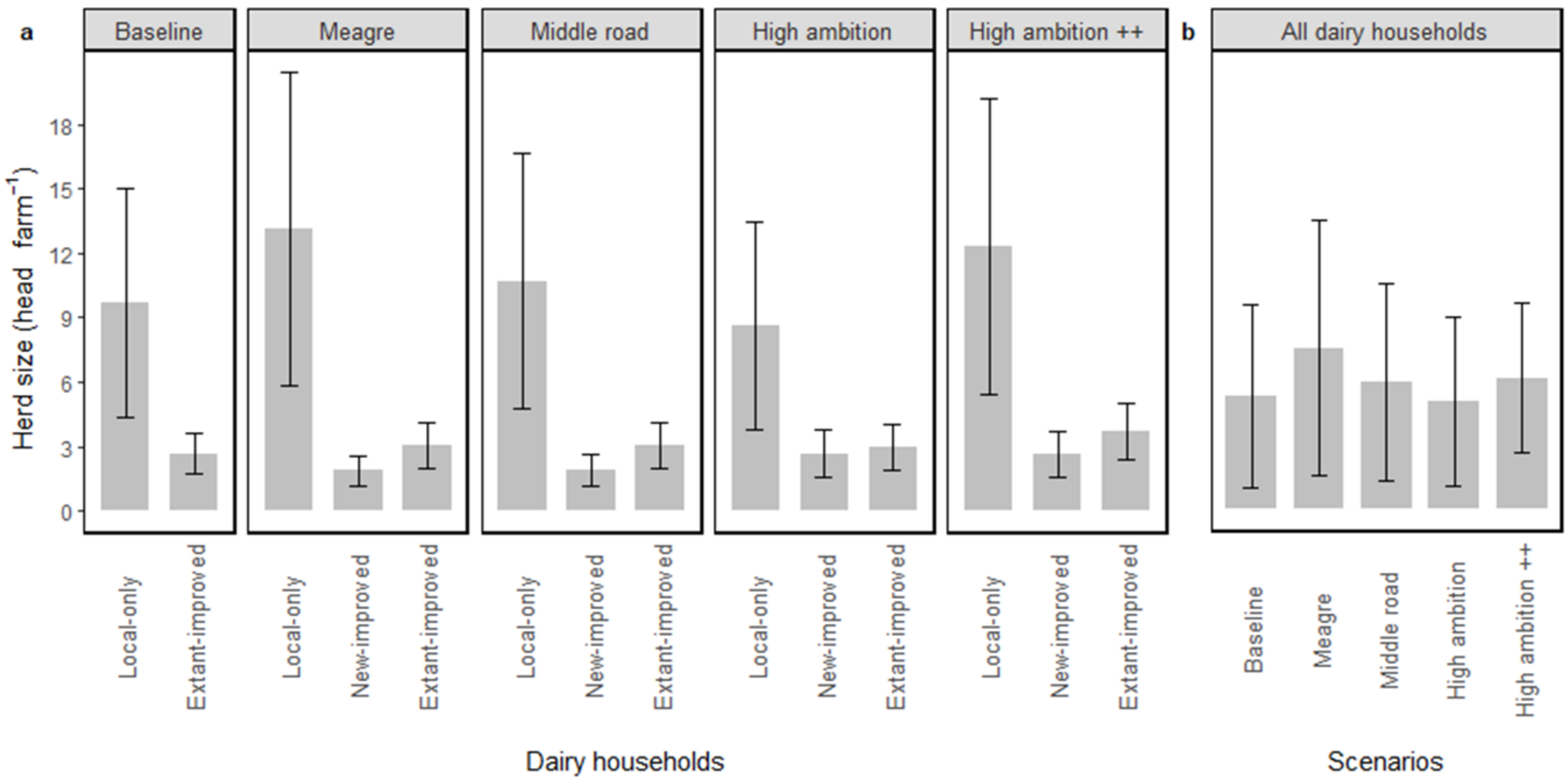

Figure 2: Herd sizes associated with dairy roadmap scenarios. Data shown represent modelled values across four districts derived from household survey (n=849). (a) Herd size for each dairy household type, and (b) Herd size for all dairy households based on the proportion of each household type within the simulated districts. Household types defined as: 'Local-only' – households rearing local cattle who do not adopt improved cattle, 'New-improved' – households rearing local cattle who adopt improved cattle in 2018, and 'Extant-improved' – households already owning improved cattle in 2018 and who maintain the same breed throughout the simulated period. Error bars indicate one standard error from the estimated value based on Monte Carlo simulations (see Methods Uncertainty).

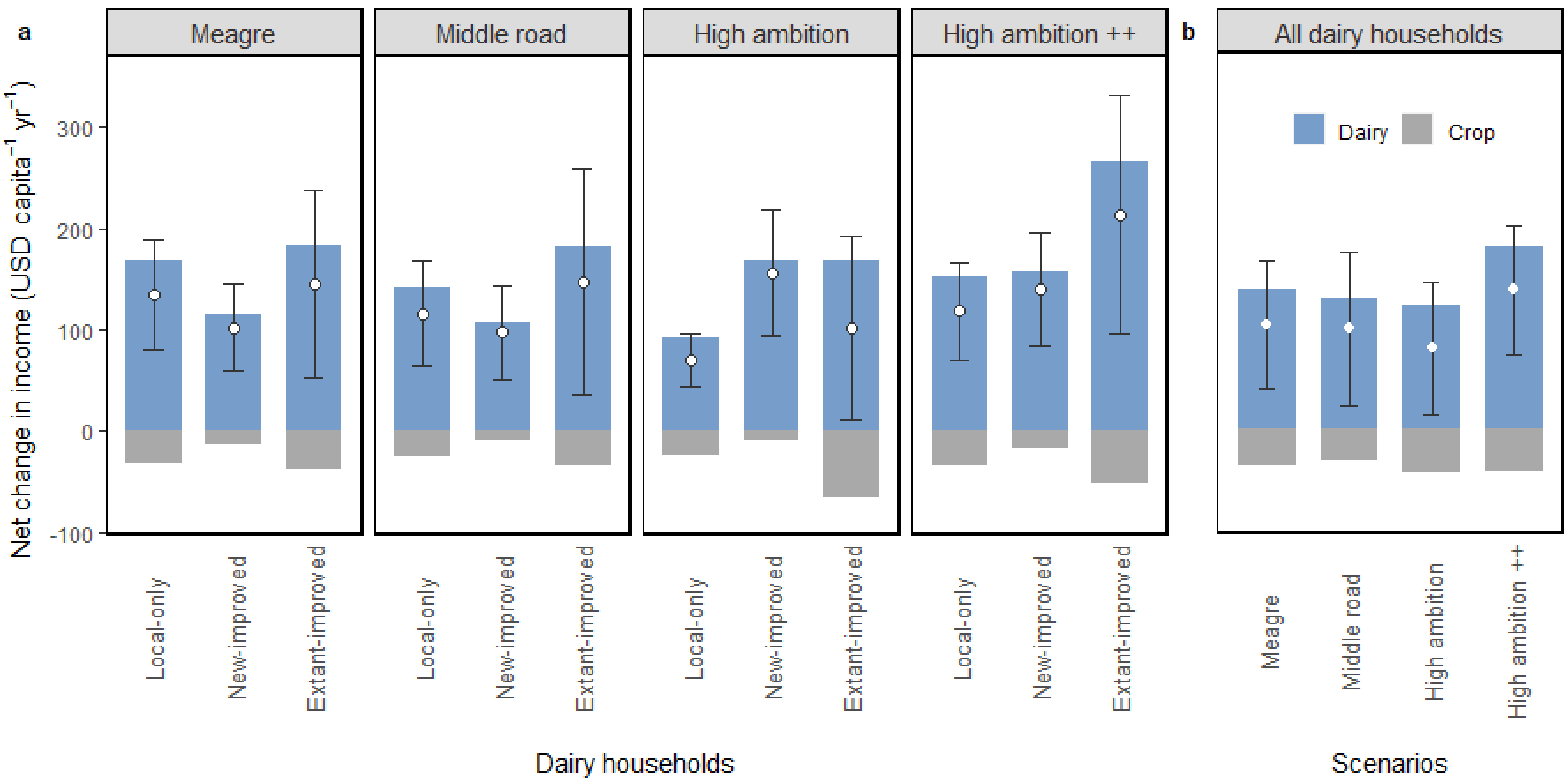

Figure 3: Changes to dairy household income resulting from roadmap scenarios. Data shown represent modelled values across four districts derived from household survey (n=849). (a) Change in income per capita for the three dairy household types by source (dairy and crop). (b) Change in income per capita for all dairy households based on the proportion of each household type within the simulated districts. Household types defined as: ‘Local-only’ – households rearing local cattle who do not adopt improved cattle, ‘New-improved’ – households rearing local cattle who adopt improved cattle in 2018, and ‘Extant-improved’ – households already owning improved cattle in 2018 and who maintain the same breed throughout the simulated period. Error bars indicate one standard error from the estimated value based on Monte Carlo simulations (see Methods Uncertainty).

Sensitivity to milk and feed prices

Widespread uptake of productivity enhancing practices among dairy farmers may lead to market feedbacks including reductions in the price of milk and/or increases in input prices. The potential impacts of reductions in milk prices and increases in concentrate feed prices were estimated using sensitivity analysis. Prices for the inputs and outputs were assumed to change by +/- 30%. Income changes among dairy households were evaluated against these price changes implemented first on a *one-at-a-time* basis and then *two-at-a-time* (changes in multiple variables). Income comparisons were made with respect to the four roadmap scenarios plus *Baseline*, thus demonstrating risks associated with the roadmap scenarios compared to the reference scenario in *Baseline* (Table 1).

Results indicated that the income impacts were most sensitive to changes in milk prices. Income growth from the scenarios relative to *Baseline* was reduced by up to 45% when milk prices declined by 30%. When milk price reductions were combined with assumed increases in prices of concentrate feed, growth in income was reduced by as much as 54% relative to Baseline. With the exception of changes in multiple prices under scenario *High ambition*, the income gains were all either positive or unchanged (not significantly different from zero) relative to *Baseline*. The roadmap scenarios would therefore have net positive income impacts despite the potential price changes considered in sensitivity analysis.

Table 1: Sensitivity analysis. Impacts of declines in milk prices and increases in feed prices on dairy household income relative to dairy roadmap and *Baseline* scenarios.

No.	Variable	% change	Scenario	Change in income (all dairy households)			
				Relative to roadmap scenario		Relative to *Baseline*	
				Absolute value (USD capita^{-1} yr^{-1})	%	Absolute value (USD capita^{-1} yr^{-1})	%
1	Maize bran, sunflower cake prices	+30	Meagre	-19.6	-9.0	+91.2	+85.3
			Middle road	-18.9	-8.8	+87.9	+82.2
			High ambition	-18.2	-9.4	+68.8	+64.3
			High ambition ++	-22.9	-8.9	+126.6	+118.4
2	Farm-gate milk price	-30	Meagre	-94.1	-43.2	+16.8	+15.7
			Middle road	-90.1	-42.2	+16.7	+15.6
			High ambition	-86.9	-44.8	+0.1	+0.1
			High ambition ++	-109.7	-42.8	+39.9	+37.3
3	1 and 2 combined	+30 & -30	Meagre	-113.3	-52.0	-2.5	-2.3
			Middle road	-108.7	-50.9	-2.0	-1.9
			High ambition	-104.9	-54.1	-17.9	-16.4
			High ambition ++	-132.5	-51.6	17.1	+16.0

Discussion

Development, self-sufficiency and mitigation

Adoption of improved breeds in the herd explored through scenarios *Middle road* and *High ambition*, allowed meeting the objective of reduced dependency and lead incrementally to lower GHG emissions (*Middle road* followed by *High ambition*) (Fig. 1b, c). Improved breeds allowed production to increase with smaller herds under scenarios *Middle road* and *High ambition* relative to *Meagre* whereby breeds remained the same or the *Baseline* that follows historical growth rates. Smaller herds in turn resulted in lower GHG emissions, in large part because of avoided emissions from land use change associated with fewer higher yielding dairy cattle. Results of scenario *High ambition* suggest that Tanzania's import dependency in the dairy sector could be reduced while fulfilling GHG targets for national climate pledges. Moreover, overall GHG reductions estimated by this study are substantially larger (20-37%) (Fig. 1c) compared to previous estimates[16,17]. These findings indicate that 4.3-7.9 Mt of CO_{2eq} could be saved every year by supporting the dairy sector achieve self-sufficiency and mitigation targets eligible for climate financing.

Costs and benefits of improved dairy breeds

Farm-level affordability has been highlighted as one of the largest barriers to scaling low-emission development practices in Africa's livestock sector[26]. Previous analyses of improved cattle adoption in Tanzania have noted a long time lag of up to 10 years until the break-even period when the dairy enterprise reaches profitability[27]. Further, large-scale technology adoption may reduce the producer price of milk, or increase prices of common inputs, in turn negating income gains from adoption, especially for late-adopters[28]. In this study, adopting households *New-improved* and *Extant-improved* benefited more than non-adopting *Local-only* (Fig 3a), which implies inherent distributional outcomes from Tanzania's dairy development roadmap. Reducing dairy dependency by adopting improved breeds would require a reduction in local cattle populations for the transition to be low-emissions. Therefore, such a strategy could affect the livelihoods of farmers dependent on local breeds, who do not adopt improved. Thus, whilst the interventions prioritised by the DDR may represent a viable pathway for the low-emissions development of Tanzania's dairy sector, these targets and priorities may not necessarily be inclusive based on current evidence, and should receive further scrutiny.

Climate change adaptation

Climate change is projected to affect dairy cattle productivity in East Africa[29], through the direct effects of heat stress followed by pathogen pressure, reducing milk yield and reproductive performance[29]. Breeding that combines tolerance to heat stress, disease and feed scarcity with high productivity are key adaptation measures. However, the need for adaptive *versus* productive traits depends on region-specific factors, most importantly temperature and rainfall. The Southern highlands and coastal regions of Tanzania have high suitability for *Bos taurus* x *Bos indicus* crosses, due to mean rainfall >1000 mm yr^{-1} and altitudes generally >1000 m above sea level, contributing to a suitable environment for dairy[13]. The Southern highlands in particular has been reported not to be exposed to rainfall anomalies[30].

Over 90% of households sampled in this region were at altitudes >1000 m above sea level, whereby annual temperatures do not exceed 21°C[18,31]. Whilst diseases such as East Coast fever and Brucellosis are widespread, veterinary services and inputs are available, which contribute to cow mortality rates among improved cattle <10%, lower than that of indigenous breeds[32]. Over 85% of farmers surveyed sprayed for ticks and dewormed their improved cows, and over 50% had vaccinated against one or more diseases in the past year[18]. However only 15% practiced feed conservation (producing silage or hay), suggesting a priority intervention area for sustaining improved cattle which depend on adequate forages year-round. The scenarios show positive net income impacts from improved breed adoption despite higher maintenance and opportunity costs from land re-allocation. As such, these findings suggest breed improvement programmes targeted to tropical and humid highlands are likely to be immune to current and near-future effects of climate change.

Implications for policy

Milk consumption in SSA is expected to triple by 2050 relative to 2000 levels, providing substantial opportunities to increase dairy revenues by meeting demand through domestic production[1]. Particularly in the value-added product segment where countries have historically been most heavily import-dependent, substituting with domestic production provides income opportunities not only for dairy producers, but throughout the entire value chain. Tanzania, relative to East African peers, is characterised by high import dependence in the value-added sector. The country's trade deficit (net imports to total consumption) is, according to FAO, 15% and 360% larger than next largest regional producers of Kenya and Ethiopia, respectively[11]. Our results showed that Tanzania's projected supply gap could be closed with net reductions in GHG emissions provided that farmers adopt improved cattle breeds where agro-ecology permits. The findings thus suggest that neighbouring countries with comparable supply gaps could similarly reduce import dependence consistentl with mitigation pledges. For example, Ethiopia has the largest herd in East Africa at 70 Million head, which is comprised of over 95% *Bos indicus* breeds[33,34], indicating potential for improved animal genetics to support climate change mitigation and national food sovereignty ambitions. Substantial parts of Ethiopia and Kenya are characterised as tropical and humid highland, whereby scope exists for realising productive synergies from genetic and practice improvements. Our findings can aid sustainable livestock development across East Africa, including from the meat sector, and could additionally be extrapolated to semi-arid environments. Different improved breeds may be required for semi-arid environments, and therefore conducting comparative analyses across regions would be particularly fruitful for further catalysing climate action throughout East Africa.

Methods

Milk production in south-coastal Tanzania

The study simulates milk production for three districts in the Tanzanian Southern Highlands region (Rungwe, Njombe and Mufindi), and one district (Mvomero) in the coastal region of Tanzania, in close proximity to the major dairy consuming region of Dar Es Salaam (the Tanzanian capital) (Fig. 4a). The study region is categorised as mid to high agroecological potential for dairy, namely mixed rainfed tropical (MRT) and humid (MRH) systems, following Robinson *et al.* (2011)[35] (Fig. 4d). These systems in the study region extend 11,700 km^2 (MRT) and 8,200 km^2 (MRH) for a total area of 19,900 km^2. Key differentiating features of these systems include, in MRT a higher proportion of grains and stover[36], which improve cattle diet quality and milk yield (see Extended data Table 1). Between 20-35% of rural households in these regions own cattle[34]: smallholder farmers are the predominant dairy producers with herds of up to 10 heads of cattle and agropastoral households' own herds of up to 30 heads of mainly local cattle. Milk produced is primarily consumed on farm, with only about 10% being sold in informal supply chains[37]. Cattle feed on diets of grazed biomass, cultivated forages, concentrates purchased on the market, and crop residues provided after the crop harvest[38]. As a result of the unimodal rainfall pattern, resulting in a six-month dry season (May-October), feed quality and quantity is highly seasonal[30]. Crop residues, concentrates, and hays or silages are used to reduce feed deficits during the dry season[38].

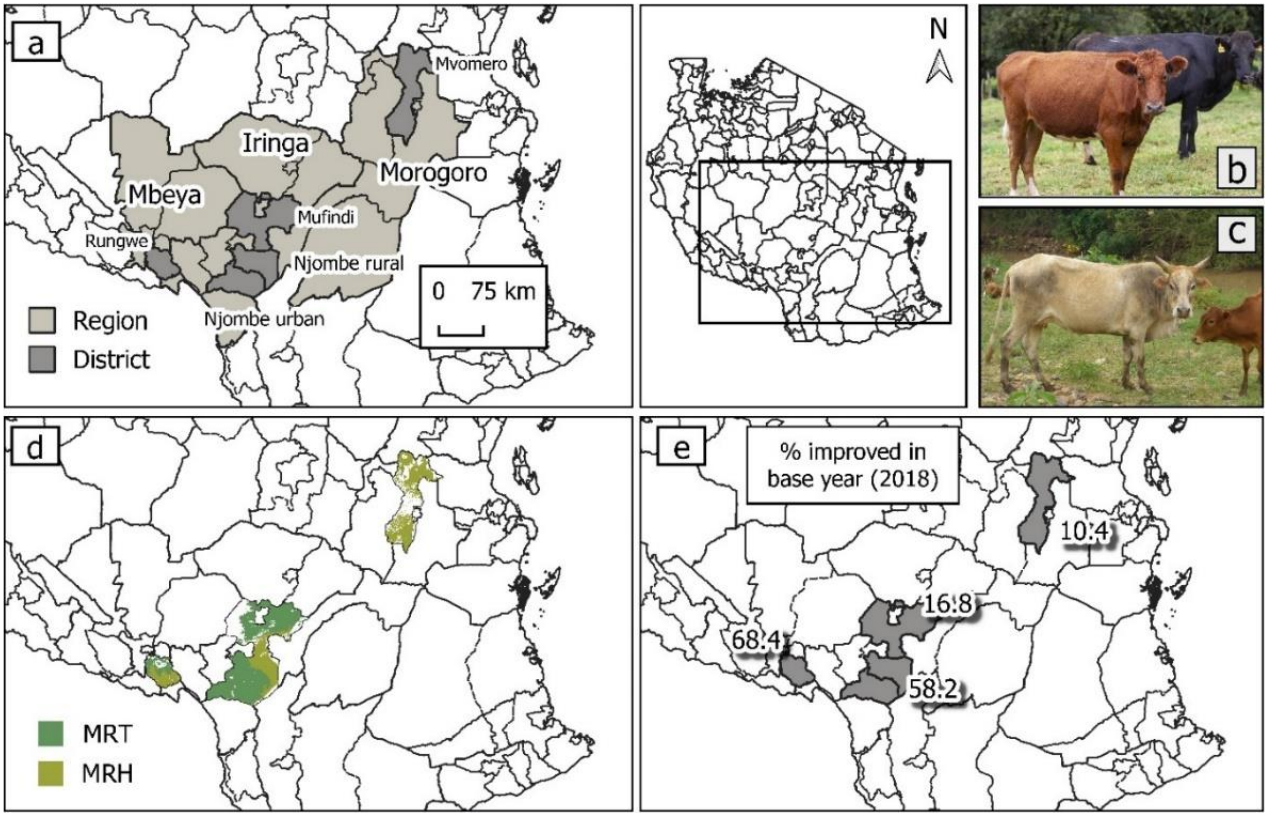

Figure 4: Geographic overview. location of study region within Tanzania showing regions and districts used in simulations, (b) improved (Bos taurus x Bos indicus) and (c) local cattle (Bos indicus) breeds considered in model, (d), production systems simulated (MRT = Mixed rainfed tropical, MRH = mixed rainfed humid), (e) dairy breed composition for base year (2018) as % improved cattle for each simulated district. Base year herd genetic compositions are based on the Greening Livestock Survey (GLS 2019). Maps and photographs attributable to authors of this paper.

Dairy farm-households

To characterise dairy farms, this study uses data from a household survey conducted in 2018, as part of IFAD's Greening livestock project. The 'Greening livestock' survey[18,31] is a survey of 1,147 crop-livestock farm-households rearing dairy cattle. The survey was administered using the Open Data Kit platform[39] (ODK Collect v1.6.1, ODK Build v0.3.0, ODK Briefcase v1.5.0) using stratified, non-blinded, random sampling across the four districts. The sample size per district was chosen as described in [36] by choosing a minimum sample required to achieve 95% statistical confidence, considering the estimated household population per district. Since the Dairy Development Roadmap selectively targets smallholder farmers for breed improvement, households owning >30 cattle were omitted from further investigation[13]. All households in the dataset owned at least one of either local or improved cattle, less than 10% of the sample own both. Households are stratified into stratum 1 (39%) with households rearing local cows only, and stratum 2 (61%) with households rearing one or more improved cows. Only 16% of stratum 2 households own local cows. Therefore, to keep the analysis simple this study does not account for revenue and expense streams associated with local cattle for stratum 2 households. Data from the two strata provide geo-referenced model inputs for cattle diets, and parameters for income accounting based on subsequent analysis in R (R v4.05, R-studio v1.2.1335)[40]. Extended data Figure 3b and c depict the main cattle breeds in the region which are referred to in this study as improved and local, respectively.

Methodology

The modelling framework links spatially-explicit data of livestock production systems and simulation modelling with farm-level income accounting (Extended data Fig. 4). Cattle production was simulated with the *Liv*estock *Sim*ulator (2020 version) (hereafter *LivSim*[41]), which simulated feeding, milk production and cattle excreta for eight simulation units: 4 districts x 2 production systems (MRT and MRH). Under the scenarios cattle populations were scaled relative to *Baseline* in relation to the 2030 milk production and breed adoption targets (see Scenarios). In each simulation unit the *Baseline* cattle populations were projected through a 12-year period between the year of the GLS survey (2018) and 2030 using historical growth rates. Land use change and GHG emissions for each scenario were quantified using a land footprint indicator and life cycle assessment[42].

In a second step, the populations of respective cattle breeds were allocated to dairy households under alternative scenarios. The quantity of dairy households in the base year (2018) in each district rearing local and improved cattle were estimated based on district livestock populations and average herd size per household (see 'Model calibration'). For *Baseline,* households maintained the same cattle breeds throughout the simulation period. The scenarios considered incremental steps towards meeting the milk production and genetics targets provided by the Tanzanian Dairy Development Roadmap, and the economic impacts of the scenarios on dairy households were accounted for based on the change in dairy income and cropland re-allocation associated with the scenarios (see ‘Income accounting’). Income sources aside from those directly impacted by the scenarios, which included

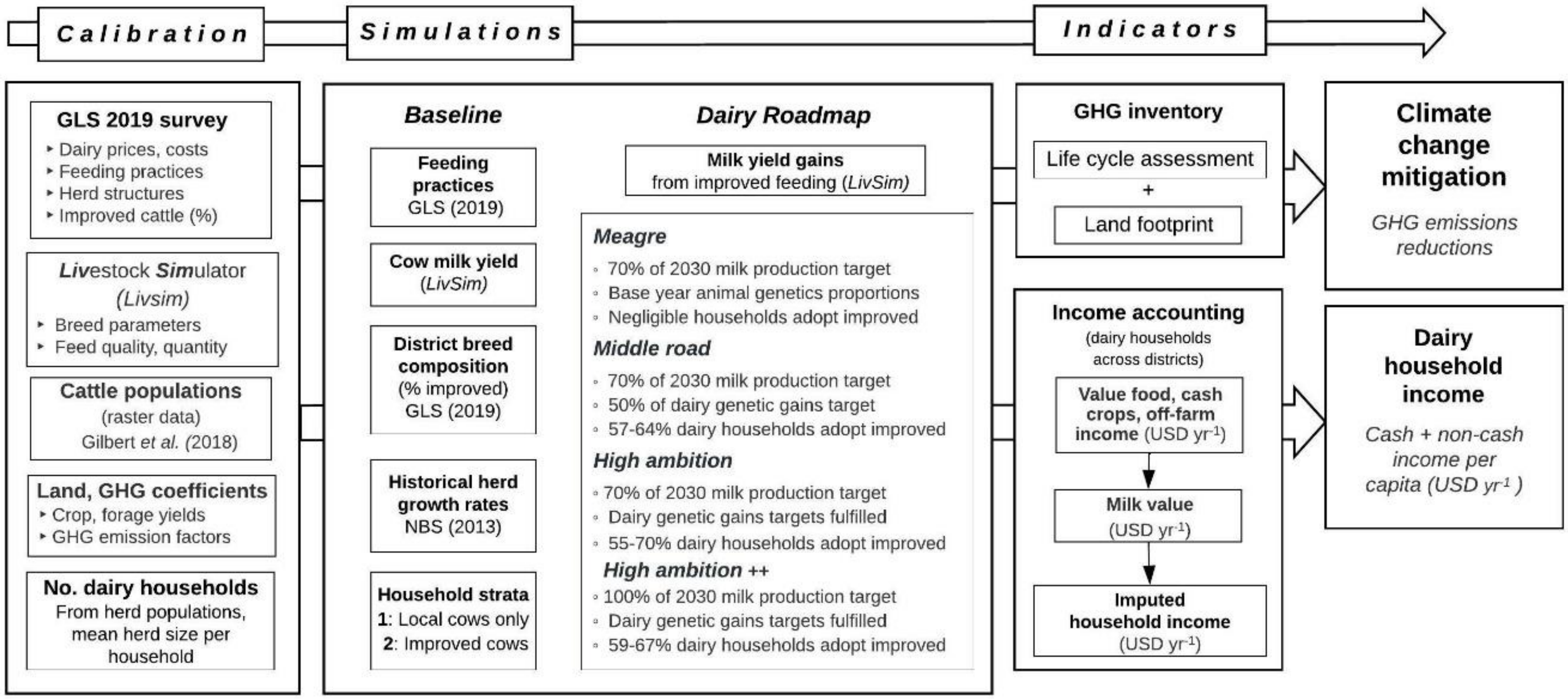

Figure 5: Model overview. Calibration involves specifying parameters from the household survey, for local and improved cattle in the livestock simulation model *LivSim*, herd population and activity data for life cycle assessment (LCA), and number of dairy households per district. Simulations represent respectively a *Baseline* (‘Business as usual’) and four scenarios involving variations of roadmap objectives. Impact indicators include dairy GHG emissions quantified using the LCA and land footprint indicator, and household income based on the milk yield, herd sizes, and input use associated with each scenario.

dairy income plus income changes from cropland re-allocation, were not considered in the analysis. The livestock production modelling and GHG quantification were conducted using Python 3.5[43]. The data used as parameters in the livestock production modelling and income accounting are available through the supplementary materials, as well as the online repositories provided through the data availability statement.

Dairy cattle simulations

LivSim was used to simulate individual cattle representing different cohorts over their lifetime. Simulations were run with a 30-day timestep whereby feed availability includes feed-specific seasonality parameters representative of the study region (SI 1 and Table S4). Six dairy cattle cohorts were simulated: cows, bulls, juvenile males, heifers, male and female calves. Simulation outputs for the six cohorts were then aggregated to the production system level. Milk production and GHG emissions (described further in section 'Life cycle assessment of milk production') were aggregated across populations of local and improved cattle and simulation units and reported as a total over all simulation units. Table S1 summarises breed coefficients used in *LivSim*; these coefficients were based on *B. indicus* (local) and *B. indicus* x *B. taurus* crosses (improved) within southern Tanzania and the East Africa region[32,44,45,46,47,48,49,50,51,52,53]. Feed quality parameters were derived from FAO's 'Feedipedia' database[54] and from representative feed nutrient sources[55,56] (Table S7). Evaluation of milk yields in the *Baseline* scenario confirmed the estimates were in line with reported values. Studies indicate local cattle in the region typically produce 500-600 L during a 250-day lactation period[53], with calving intervals ranging from 450 to 600 days[53], implying annualized milk yields of 305-490 L yr^{-1}. The simulated regional average milk yield for local cattle weighted by production system of 333±50 L yr^{-1} is thus within the observed ranges. Improved cattle typically produce 1350-2200 L during a 305-day lactation period[32,53], with calving intervals ranging from 450-600 days[32,53], resulting in annualized milk yields of 945-2,010 L yr^{-1}. The simulated regional average milk yield for improved cattle weighted by production system was 1,472±221 L yr^{-1}, thus also consistent with observed values for the study region.

Dairy land footprint

The land footprint was calculated with feed biomass, land use, yield and feed use efficiencies of each feedstuff[42]. Changes in herd size for each scenario resulted in changes to the demand for cropland and grasslands and land use transitions which were used to calculate CO_2 emissions in the LCA (see 'CO_2 emissions from land use change'). The land footprint considered main feedstuffs: Maize bran and sunflower cake are the two main dairy supplements in south and coastal Tanzania[38]. Forages included native grasses, managed pasture, and Napier grass (*Pennisetum purpureum*) as the high-quality feed used by dairy households in the region[38,18]. Maize stover is the most consumed crop residue. These feeds are sourced domestically[38,57] and thus biomass yields, processing ratios (the fraction of compound feed derived per unit grain or oilseed), and feed use efficiencies (the fraction of biomass grazed or harvested) were based on local and regionally representative data (Table S2). Yield growth of feed crops were projected throughout the simulation period following historical annual growth rates of 3.4% for maize and 4.1% for sunflower[58].

Model calibration

Populations of cattle for the base year were obtained from a gridded livestock population dataset[59], extrapolated from the source year (2012) with district-level historical herd growth rates. The ratio of dairy to total cattle was total cattle minus beef cattle and oxen taken from census data[60]. For local and improved breeds, the ratio of each cohort as a fraction of the respective herd were from GLS (2019)[18] (Table S3). Breed composition for 2018 for each district is shown in Figure 4e. This population and herd structure were then mapped to spatial datasets of MRT and MRH production systems and aggregated, resulting in the base year cattle populations by cohort for each of local and improved herds for every simulation unit.

Household census data in Tanzania does not distinguish between households rearing dairy cattle from other agricultural households. Households rearing each breed were therefore estimated from the cattle population[59] and survey data[18], using respective herd populations, and mean herd size per household strata as:

$$Dairy\ households_{d,s} = \frac{Cattle\ population_{d,s}}{Mean\ cattle\ per\ household_{d,s}} \quad (1)$$

Where *Dairy households* is the number of households rearing dairy cattle, local or improved, *cattle population* is the population of dairy cattle, *Mean cattle per household* is the average head of cattle in the survey year for a given household, and indices *d* and *s* represent districts and household strata, respectively. The cattle populations for respective breeds, local and improved, in equation (1) mapped to stratum 1 and 2 respectively. This equation therefore related the number of households owning a given breed, local or improved, to the number of each breed in the population.

Scenarios

Baseline. Populations of cattle grow at historical annual rates of 3.2% for local and 4.3% for improved. These were based on agricultural census data for the period 2003-2008 which are consistent with values observed for the 2008-2020 period, thus reflecting long-term growth rates of cattle populations in the study region[61,34]. Cattle diets used in the *Baseline* were taken from the household survey for households with local *vs* improved cattle. Detailed diets are provided in Table S3.

Under the roadmap scenarios, herd sizes were scaled based on the requirements to meet milk production targets in each district, given the milk yields and breed compositions per scenario. Scenarios *Meagre*, *Middle road*, and *High ambition* were based on 70% of the milk production targets and *High ambition ++* considers reaching production targets in full in each district. Herd sizes to meet the production target with milk yields and breed composition were determined by multiplying the herd size under *Baseline* by a scaling factor, as follows:

$$H_{d,l} = T_{d,l} \times \frac{\sum_s Cows_{b,l} \times Frac\_s\_b_{s,l} \times Yield_{b,s,l}}{\sum_s Cows_{b,l} \times Frac\_s\_r_{s,l} \times Yield_{r,s,l}} \qquad (2)$$

Where *H* (unitless) is a herd scaling factor for district *d* and production system *l* (MRT and MRH), *T* (unitless) is milk production growth over *Baseline*, *Cows* is the population in each scenario, *Frac_s* are the fractions of local or improved cattle in the *Baseline* ('_b') or roadmap scenarios ('_r'), and *Yield* is the milk yield in kg

FPCM cow^{-1} yr^{-1} under the baseline ('b') and roadmap ('r') scenarios for either local or improved cattle in a given simulation unit.

Cattle diets under the roadmap scenarios were designed to reflect the types of feeding practice changes the roadmap has prioritized. These involved increased feeding of silages and hays to reduce seasonal feed deficits, greater year-round provision of high-quality forages, and supplementation with energy and protein concentrates[12]. The diets under all the roadmap scenarios were implemented for cows only and were assumed constant across the four scenarios. Feeding changes involved greater provision of *Napier* grass year-round and as silage during the dry season, and supplementation with maize bran and sunflower cake according to the lactation cycle of the animal (see full summary in Table S4).

Production and genetics targets

Scenarios *Meagre*, *Middle road*, and *High ambition* represented genetic gains outcomes representing the variability between the values observed in 2018 and the targets defined under the DDR, at respectively 0, 50%, and 100% of the targets for scenarios *Meagre*, *Middle road*, and *High ambition* respectively (Extended Data Table 2). Production targets were specified respectively for highlands and coastal districts by extrapolating the DDR projected milk production growth rates (as an annualised percentage) for respective regions to 2030 using a linear growth rate. The resultant level of production growth is defined as a percentage increase over the base model year (2018), equal to 234% (highlands) and 152% (coastal) the base year (2018) milk production values.

Animal genetics targets and household adoption were similarly aligned with the DDR which stipulate targets of 60% (highlands) and 27% (coastal) improved cattle as a percentage of all cattle in a given district, and 60% (highlands) and 45% (coastal) of dairy producing households adopting in a given district. The household adoption rates under these scenarios were coordinated with the targets of the DDR: the percentage of the adoption rate fulfilled under each scenario was proportional to the genetics target of the respective scenario. That is, under *Meagre* no households adopted new improved cattle; under *Middle road* the adoption rate fulfilled 50% of the DDR target; under *High ambition* the adoption rate entirely fulfilled the DDR adoption targets. Under *High ambition++* the quantity of households adopting were assumed to be the same as under *High ambition*.

Dairy greenhouse gas emissions

Direct emissions from cattle and feed production were based on IPCC (2006) Tier 2 and 3 equations[62]. Emission factors were based on IPCC (2006) including updated estimates of the 2019 refinement guidelines[63] (Table S9). The CO_2 emissions associated with the use of fossil energy for feed and N fertiliser inputs were calculated based on the amount of maize bran and sunflower cake consumed by the dairy cattle. N-fertiliser application rates were simulated as a linear trendline based on FAO country level fertilizer use data[64]. The base year (2018) application rates were set consistent with typically observed application rates for the south and coastal regions of Tanzania, taking values of 20 kg N ha^{-1} yr^{-1} for maize and sunflower, and 10 kg N ha^{-1} yr^{-1} for food crops[65,66]. Soil N_2O fluxes per land use type are shown in Table S2. Co-product allocation for soil N_2O fluxes were based on mass allocation factors (i.e. the proportion of total biomass produced actually devoted to dairy feed). Co-product allocation between FPCM and meat were based on the allocation formula of the International Dairy Federation[67]. Simulated milk production was converted to FPCM by standardising to 4.0% fat and 3.3% protein[67]. Meat production was calculated as carcass weight of culled adult females, and young males either culled or sold as is common practice by Tanzanian dairy farmers[32]. Liveweights at time of culling were based on simulated liveweight from *LivSim,* and a dressing of 52%[32] was applied to calculate dairy-meat output. Details on methods and procedures used in the LCA are in SI 2.

CO_2 emissions from land use change

LUC was calculated assuming two transition pathways: *cropland expansion,* where croplands displace grasslands, and *grassland expansion*, where grasslands displace other native ecosystems. Changes in dairy feed demand associated with changes in diets and breeds increased areas dedicated to croplands for the scenarios. However, the decline in grassland areas were higher than the increase in cropland areas, and therefore the total dairy land footprint declined. Dairy feed intake and corresponding land use changes are shown in Extended Data Fig. 2. The CO_2 emissions resulting from LUC were based on carbon stock differences between land uses, as calculated from spatially-explicit land cover and carbon density data, described in SI 2 and reported in Table S2. The actual amount of grassland converted from native ecosystems was calculated by relating the area required for each scenario, and the spatially-explicit availability of grasslands[69], described further in SI 3.

Income impacts

Income impacts of the scenarios were reported for each dairy household based on the net change in dairy income plus the change in crop income resulting from increases (decreases) in land dedicated to food or cash crops.

$$\textit{Net income change}_{d,\mathrm{t}} = \textit{Change in dairy income}_{d,\mathrm{t}} + \text{Change in } \textit{crop income}_{d,\mathrm{t}} \quad (3)$$

Where *Net income change*$_d$ is the net change in dairy and crop enterprise income for a dairy household of type t in district d relative to the *Baseline* scenario, *Change in dairy income*$_{d,\mathrm{t}}$ is the increase (decrease) to income resulting from a change in dairy enterprise income in USD yr^{-1}, and *Change in crop income*$_{d,\mathrm{t}}$ is the decrease (increase) in annual crop income in USD yr^{-1} resulting from an increase (decrease) in land devoted to forage production. The indices d and t represent the four districts and three household types, respectively.

Dairy income under each scenario was calculated using mean number of cattle per household type for each district and stratum and simulated milk yields per cow (Extended Data Table 1). Income for each district was calculated using weighted average milk yields of MRT and MRH systems per district, based on the relative production between the two systems (Extended Data Table 1). Milk income was calculated as the market value of annual milk production per household, net of costs related to acquiring improved heifers (for *New-improved*), and variable costs of feeding and animal husbandry. The cash value of production from the dairy enterprise was estimated based on annual feed and animal husbandry cash expenses and (for *New-improved*) the one-time cost of purchasing improved heifers, spread evenly over the 12-year simulation period according to:

$$Dairy\ Income_{d,t} = Milk\ value_{d,t} - Dairy\ expenses_{d,t} - Cost\ of\ Heifers_{d,t} \times \left(\frac{1}{12}\right) \quad (4)$$

where *Dairy income*$_{d,t}$ is the annual cash value of production for the dairy enterprise in USD yr^{-1} for a dairy household of type t in district d, *Milk value* is the monetary value of milk production from cows in the herd in USD yr^{-1}, *Dairy expenses* are the variable cash expenses for the dairy herd in USD yr^{-1}, and *Cost of Heifers* is the cost of acquiring new improved heifers in USD for *New-improved* households. For *New-improved,* no revenue is received until a purchased heifer(s) calves. Parameters in equation (4) were then updated reflecting those of stratum 2 households (rearing improved cattle), thus accounting for changes in input use intensity associated with rearing improved *versus* local cattle. *Milk value* was thus based on the number of cows in the herd multiplied by milk yield per cow (Table 1), multiplied by the farm gate milk price in USD $litre^{-1}$. Milk yields were converted to litres using a density of 0.97 litres kg^{-1}. Table S11 summarises the farm gate milk prices and other variable input expense parameters used in equation 4, obtained from the survey[18]. The price of an improved heifer was based on values reported by survey respondents: Mufindi, 397.7±78.1; Mvomero, 254.1±57.9; Njombe 479.5±115.6; Rungwe, 397.7±220.7 USD $head^{-1}$. The market prices of sunflower cake and maize bran were based on a sample of feed processors conducted for south and coastal regions of Tanzania[70], which in the base year took values of 0.25 and 0.21 USD kg^{-1} respectively.

Change in crop income was calculated based on the total area dedicated to crops in the base year, and accounting for the change in crop area associated with an increase (decrease) in area allocated to planted pasture in 2018, and any associated sowing costs. The *Crop income* for household type t in district d was thus calculated as:

$$\textit{Change in crop income}_{d,t} = \textit{Base year crop income}_{d,t} + \textit{Mean net crop margin}_{d,t} \times \textit{Change in forage area}_{d,t} - \textit{Forage sowing cost}_{d,t} \times \left(\frac{1}{12}\right) \quad (5)$$

where *Base year Crop income*$_{d,t}$ is the total income (USD yr^{-1}) from crop production in 2018, *Mean net crop margin* is the average margin (USD yr^{-1}) per cropping hectare, *Change in forage area* is the change in area (ha) devoted to cultivated forages, and *Forage sowing cost* is the cost of sowing newly planted forages. The crop margins used to calculate foregone crop income are calculated from the survey data based on reported market prices and variable inputs (Extended data Table 3). Land dedicated to planted forages per household type in the base year were based on herd sizes (Extended Data Table 3) per household, quantity of feed intakes of the respective forages (Table S3), and their yields (Table S2). The *Forage sowing cost* assumed a sowing rate of 10 kg seeds ha^{-1} and a price of seeds of 28 USD kg^{-1} [71,72].

Monetary values reported in the survey in Tanzanian shillings were converted to USD using a 2018 exchange rate of 2,263 TSh USD^{-1}. All prices in income accounting other than heifers were set equal to the final model year prices which were estimated based on the national average annual inflation rate of 4.1%[75]. Heifer prices were based on the 2018 values, and costs of replacement animals in subsequent years were accounted for in the animal husbandry costs for each household (Extended Data Table 4). Changes to income results were then divided by average household sizes (Extended Data Table 3) to reflect the per capita values.

Uncertainty

Monte Carlo simulations were conducted quantifying uncertainty of the two main outcome indicators of GHG emissions and household income. Parameters used to estimate each indicator were drawn randomly from their probability distributions and the mean and variance of the resulting simulations were used as the basis for uncertainty. As GHG emissions sources used in this study were primarily based on Tier 2 estimates with relatively little uncertainty (see Table S10), GHG emissions uncertainty was reported at the 95% confidence level. Income uncertainty is reported as one standard error from the mean. For the Monte Carlo simulations, All input parameters are assumed to be normally distributed and their standard errors (%) are specified based on the expected variability throughout the study region, described below.

Milk yield uncertainty

Uncertainty in *LivSim* estimated feed intake and milk yield were accounted for based on (i) variability in breed parameters, and (ii) variability in feed quality within the study region. Breed parameter uncertainty included lactation period, lactation milk yield, age at first calving, and length of dry period (Table S1). Uncertainty in feed quality parameters included dry matter digestibility, metabolisable energy, and crude protein (Table S7). Milk yield uncertainty from breed and feed variability was estimated as 24% and 21% (% standard error) for local and improved cattle, respectively, under the *Baseline* diets. Under the DDR scenario diets, uncertainty on milk yield was 18% and 19% (local and improved respectively).

GHG emissions uncertainty

Standard errors of GHG emission factors were based either on IPCC African defaults or based on reported values from sources representative of the southern highlands and coastal regions of Tanzania, summarised in Table S6. Under the *Baseline,* uncertainty included emission factors, feed on offer per head, biomass yields, and cattle populations. In each subsequent simulation, for which cattle populations and feed intakes were specified in relation to *Baseline*, only emission factor and biomass yield uncertainty were accounted for.

Income uncertainty

Uncertainty in imputed income per household included variability in dairy income and uncertainty in changes in crop income from forage land re-allocation. Sources of variability in dairy income included the milk price, milk yield per cow (kg yr^{-1}), and dairy expenses as reported in Extended Data Table 4. Uncertainty in crop margins were based on standard deviations reported in Extended Data Table 3. Uncertainty was then aggregated for the three household types for the entire region, and as an average for all dairy households in the simulation. When aggregating household income to the population level, error ranges considered both uncertainty in income per household type and number of each household type per district. The latter was calculated based on the standard error of the proportion of household types within the population, calculated as $\sqrt{\mathrm{p}\,(1-\mathrm{p})\,/\mathrm{n}}$, where p is the sampled proportion of a given household for either stratum 1 or 2 in one of the four household samples, and n is the sample size for a given district as reported in Extended Data Table 3.

References

1. MMP (Malabo Montpellier Panel). Meat, Milk and More: Policy Innovations to Shepherd Inclusive and Sustainable Livestock Systems in Africa. Dakar, Senegal: International Food Policy Research Institute/AKADEMIYA2063. Malabo Montpellier Panel. Kigali, Rwanda. 94 pp. (2020).

2. FAO (Food and Agriculture Organization). Value of agricultural production. (2022). [Accessed at https://www.fao.org/faostat/en/#data/QCL].

3. Jayne, T. & Sanchez, P.A. Agricultural productivity must improve in sub-Saharan Africa. *Science* **372**, 1045-1047 (2021).

4. Dangal, S.R.S. *et al.* Methane emission from global livestock sector during 1890-2014: Magnitude, trends and spatiotemporal patterns. *Glob. Change Biol.* **23**, 4147–4161 (2017).

5. Mottet, A. *et al*. Climate change mitigation and productivity gains in livestock supply chains: Insights from regional case studies. *Reg. Env. Change* **17**(1), 129–141 (2016).

6. Valin, H. *et al*. Agricultural productivity and greenhouse gas emissions: trade-offs or synergies between mitigation and food security? *Environ. Res. Lett.* **8**, 035019 (2013).

7. González-Quintero, R. *et al*. (2022). Yield gap analysis to identify attainable milk and meat productivities and the potential for greenhouse gas emissions mitigation in cattle systems of Colombia. *Agric. Syst.* 195, 103303.

8. FAO. Crops and Livestock Products. (2022). [Accessed at http://www.fao.org/faostat/en/#data/QCL].

9. Ledo, J., *et al*. Persistent challenges in safety and hygiene control practices in emerging dairy chains: The case of Tanzania. *Food Control* **105** 164-173 (2019).

10. Häsler, B., *et al*. Integrated food safety and nutrition assessments in the dairy cattle value chain in Tanzania. *Glob. Food Sec.* **18** 102-113 (2018).

11. FAO. Supply utilization accounts. Accessed at [http://www.fao.org/faostat/en/#data/TCL]. (2022).

12. Michael, S., *et al.* Tanzania Livestock Master Plan. Nairobi, Kenya: International Livestock Research Institute (ILRI). Addis Ababa, Ethiopia. 82 pp (2018).

13. URT (United Republic of Tanzania). Tanzania Livestock Sector Analysis (2016/2017 – 2030/2031). United Republic of Tanzania Ministry of Livestock and Fisheries. 157 pp. Accessible at [https://www.mifugouvuvi.go.tz/uploads/projects/1553602287-LIVESTOCK%20SECTOR%20ANALYSIS.pdf]. (2017).

14. Nicholson, C., *et al.* Assessment of investment priorities for Tanzania's dairy sector: Report on activities and accomplishments. Nairobi, Kenya: ILRI. (2021).

15. Chagunda, M.G.C., Romer, D.A.M., & Roberts, D.J. (2009). Effect of genotype and feeding regime on enteric methane, non-milk nitrogen and performance of dairy cows during the winter feeding period. *Livest. Sci.* **122**, 323-332 (2009).

16. Notenbaert, A., *et al.* Towards environmentally sound intensification path/ways for dairy development in the Tanga region of Tanzania. *Reg. Environ. Change* **20**, 138, 1-14 (2020).

17. Yesuf, G.A., *et al.* Embedding stakeholders' priorities into the low-emission development of the East African dairy sector. *Env. Res. Lett.* **16** 064032 (2021).

18. GLS (Greening Livestock Survey). International Livestock Research Institute. Nairobi, Kenya. Accessed at [https://data.ilri.org/portal/dataset/greeninglivestock]. (2019).

19. URT (United Republic of Tanzania). Intended Nationally Determined Contributions. Dar es Salaam, Tanzania. (2021). Accessed at [https://unfccc.int/sites/default/files/NDC/2022-06/TANZANIA_NDC_SUBMISSION_30%20JULY%202021.pdf]

20. Ndung'u, P.W. *et al.* Farm-level emission intensities of smallholder cattle (*Bos indicus*; *B. indicus–B. taurus* crosses) production systems in highlands and semi-arid regions. *Animal.* **16,** 1, 100445.(2022).

21. Goopy, J.P. *et al*. Severe below-maintenance feed intake increases methane yield from enteric fermentation in cattle. *Br. J. Nutr.* **123**, 1239–1246 (2020)

22. Goopy, J.P. *et al*. A new approach for improving emission factors for enteric methane emissions of cattle in smallholder systems of East Africa – Results for Nyando, Western Kenya. *Agric. Syst.* **161**, 72-80 (2018).

23. FAO New Zealand (FAO & New Zealand Agricultural Greenhouse Gas Research Centre). Supporting low emissions development in the Tanzanian dairy cattle sector—Reducing enteric methane for food security and livelihoods. Rome. 34 pp (2019).

24. Gerssen-Gondelach, S.J., *et al.* Intensification pathways for beef and dairy cattle production systems: Impacts on GHG emissions, land occupation and land use change. *Agric. Ecosyst. & Environ.* **240**, 135–147 (2017).

25. Havlik, P., *et al.* Climate change mitigation through livestock system transitions. *Proc. Natl. Acad. Sci.* **111**, 3709-3714 (2014).

26. Herrero, M., *et al.* Greenhouse gas mitigation potentials in the livestock sector. *Nat. Clim. Change* **6**, 452–461 (2016).

27. Dizyee, K., Baker, D., & Omore, A. Upgrading the smallholder dairy value chain: a system dynamics *ex-ante* impact assessment in Tanzania's Kilosa district. *J. Dairy Res.* **86**, 4, 440–449 (2019).

28. Simões, A.R.P., Nicholson, C.F., Novakovicc, A.M., & Protil, R.M. Dynamic impacts of farm-level technology adoption on the Brazilian dairy supply chain. *Int. Food Agribusiness Manag. Rev.* **23**, 1 (2020).

29. Rahimi, J. *et. al.* Heat stress will detrimentally impact future livestock production in East Africa. *Nat. Food.* **2**, 88–96 (2021).

30. Mbululo, Y., & Nyihirani, F. Climate Characteristics over Southern Highlands Tanzania. *Atmos. Clim. Sci.* **2**, 4, 454-463 (2012).

31. Kihoro, E.M., Schoneveld, G.C., & Crane, T.A. Pathways toward inclusive low-emission dairy development in Tanzania: Producer heterogeneity and implications for intervention design. *Agric. Syst.* **190** (2021).

32. Mruttu, H. *et al.* Animal genetics strategy and vision for Tanzania. Nairobi, Kenya: Tanzania Ministry of Agriculture, Livestock and Fisheries and International Livestock Research Institute (ILRI). Addis Ababa, Ethiopia. 24 pp. (2016).

33. CSA (Central Statistical Agency). Agricultural sample survey 2018/19 report on livestock and livestock characteristics (private peasant holdings). Statistical bulletin 588. 99p. (2019).

34. NBS (National Bureau of Statistics). 2019/20 National sample census of agriculture main report. Tanzania National Bureau of Statistics. Dodoma, Tanzania. 321 pp (2022).

Methods references

35. Robinson, T.P. *et al.* Global Livestock Production Systems. Food and Agriculture Organization of the United Nations, International Livestock Research Institute, Rome, Italy. 171 pp (2011).

36. Herrero, M. *et al.* Biomass use, production, feed efficiencies and greenhouse gas emissions from global livestock systems. *Proc. Natl. Acad. Sci.* **110,** 52, 20888–20893 (2013).

37. URT. (United Republic of Tanzania). Baseline study of the Tanzania dairy value chain. United Republic of Tanzania Ministry of Agriculture, Livestock and Fisheries. 36 pp. (2016).

38. Mbwambo, N., Nandonde, S., Ndomba, C. & Desta, S. Assessment of animal feed resources in Tanzania. Nairobi, Kenya: Tanzania Ministry of Agriculture, Livestock and Fisheries and International Livestock Research Institute (ILRI). Nairobi, Kenya. 24 pp (2016).

39. International Conference on Information and Communication Technologies and Development. Proceedings of the 4th ACM/IEEE International Conference on Information and Communication Technologies and Development. 18, 1-12. (2010).

40. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. (2022). Accessed at [https://www.r-project.org]

41. Rufino, M.C. *et al*. Lifetime productivity of dairy cows in smallholder farming systems of the Central highlands of Kenya. *Animal* **3**, 1044-1056 (2009).

42. Hawkins, J. *et al.* Feeding efficiency gains can increase the greenhouse gas mitigation potential of the Tanzanian dairy sector. *Sci. Rep.* **11**, 4190 (2021).

43. PSW (Python Software Foundation). About Python Software Foundation. (2019). Accessible at [https://www.python.org/psf/]

44. Kashoma, I. P. B. *et al.* Predicting body weight of Tanzania shorthorn zebu cattle using heart girth measurements. *Livest. Res. Rural. Dev.* **23** (2011).

44. Galukande, E. B., Mahadevan, P., & Black, J. G. Milk production in East African zebu cattle. *Anim. Sci*. **4**, 329–336 (1962).

48. Gillah, K.A., Kifaro, G.C., & Madsen, J. Effects of pre partum supplementation on milk yield, reproduction and milk quality of crossbred dairy cows raised in a peri urban farm of Morogoro town Tanzania. *Livest. Res. Rural. Dev.* **26** (2014).

49. Njau, F.B.C, Lwelamira, J., & Hyandye, C. Ruminant livestock production and quality of pastures in the communal grazing land of semi-arid central Tanzania*. Livest. Res. Rural. Dev.* **8** (2013).

50. Mwambene, P.L. *et al.* Selecting indigenous cattle populations for improving dairy production in the Southern Highlands and Eastern Tanzania. *Livest. Res. Rural. Dev*. **26** (2014).

51. Rege, J.E.O. *et al.* cattle of Kenya: Uses, performance, farmer preferences, measures of genetic diversity and options for improved use. Animal Genetic Resources Research 1. ILRI (International Livestock Research Institute), Nairobi, Kenya. 103 pp. (2001).

52. Beffa, L.M. Genotype × Environment Interaction in Afrikaner Cattle. Doctoral thesis, Faculty of Natural and Agricultural Sciences, Department of Animal, Wildlife and Grassland Science. University of the Free State, Bloemfontein, South Africa, 128 pp (2005).

53. Meaker, H.J., Coetsee, T.P.N., & Lishman, A.W. The effects of age at 1st calving on the productive and reproductive-performance of beef-cows. *S. Afr. J. Anim. Sci*. **10**, 105-113 (1980)

54. Chenyambuga, S. W., & Mseleko, K. F. Reproductive and lactation performances of Ayrshire and Boran crossbred cattle kept in smallholder farms in Mufindi district, Tanzania. *Livest. Res. Rural. Dev*. **21**, 100 (2009).

55. Ojango, J.M.K. *et al.* Dairy production systems and the adoption of genetic and breeding technologies in Tanzania, Kenya, India and Nicaragua. *Anim. Genet. Resour.* **59**, 81–95 (2016).

56. FAO. Feedipedia - Animal Feed Resources Information System - INRA CIRAD AFZ and FAO. [Accessed at https://www.feedipedia.org/.] (2021). [Accessed 2021]

57. Lukuyu, B. *et al.* (eds). Feeding dairy cattle in East Africa. East Africa Dairy Development Project, Nairobi, Kenya. 95 pp (2012).

58. Rubanza, C.D.K. *et al.* Biomass production and nutritive potential of conserved forages in silvopastoral traditional fodder banks (Ngitiri) of Meatu District of Tanzania. *Asian-Aust. J. Anim. Sci.* **19**, 978–983 (2006).

59. FAO. New food supply balances. [Accessed at http://www.fao.org/faostat/en/#data/FBS]. (2021).

60. FAO. Crop data for the United Republic of Tanzania. [Accessed at http://www.fao.org/faost at/en/#data/QC]. (2021).

61. Gilbert, M. *et al.* Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010. *Sci. Data.* **5**, 180227. (2018).

62. NBS (National Bureau of Statistics). 2014/15 Annual agricultural sample survey report. The United Republic of Tanzania. Dar es Salaam, Tanzania. 85 pp (2016).

63. NBS (National Bureau of Statistics). Basic Data for Livestock and Fisheries. The United Republic of Tanzania Ministry of Livestock and Fisheries. Dar es Salaam, Tanzania. 135 pp (2013).

64. IPCC. IPCC Guidelines for National Greenhouse Gas Inventories, vol. 4. Agriculture, Forestry and Other Land Use. IGES, Hayama, Japan. 87 pp (2006).

65. IPCC (Inter-governmental Panel on Climate Change) 2019 Refinement to the IPCC. (2014). IPCC: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 (2019).

66. FAO. New food supply balances. [Accessed at https://www.fao.org/faostat/en/#data/RFN]. (2022).

67. Hutton, M.O. *et al.* Toward a nitrogen footprint calculator for Tanzania. *Env. Res. Lett.* **12**, 034016 (2017).

68. IFDC (International Fertilizer Development Center). Tanzania Fertilizer Assessment, in support of The African Fertilizer and Agribusiness Partnership. IFDC.42 pp. Accessed at [http://tanzania.countrystat.org/fileadmin/user_upload/countrystat_fenix/congo/docs/Tanzania%20Fertilizer%20Assessment%202012.pdf]. (2012).

69. IDF (International Dairy Federation). Bulletin 479. (2015). A common carbon footprint approach for the dairy sector. The IDF guide to standard life cycle methodology. International Dairy Federation. Brussels, Belgium. 63 pp. Available at [https://www.fil-idf.org/wp-content/uploads/2016/09/Bulletin479-2015_A-common-carbon-footprint-approach-for-the-dairy-sector.CAT.pdf]

70. Mruttu, H. *et al.* Animal genetics strategy and vision for Tanzania. Nairobi, Kenya: Tanzania Ministry of Agriculture, Livestock and Fisheries and International Livestock Research Institute (ILRI). Addis Ababa, Ethiopia. 24 pp. (2016).

71. Bruzzone, L, Bovolo, F., & Arino, O. European Space Agency Land cover climate change initiative. ESA LC CCI data: High resolution land cover data via Centre for

Environmental Data Analysis. Accessed at [https://climate.esa.int/en/projects/high-resolution-land-cover/.]. (2021).

72. Kilimo Trust. Characteristics of markets for animal feeds raw materials in the East African community: focus on maize bran and sunflower seed cake. Kilimo Trust. Kampala, Uganda. 50 pp. (2017).

73. Ngunga, D. & Mwendia, S. Forage Seed System in Tanzania. A Review Report. Alliance of Biodiversity and CIAT. 13 pp (2020).

74. Nkombe, B.M. Investigation of the potential for forage species to enhance the sustainability of degraded rangeland and cropland soils. MSc thesis. Ohio State University. 162 pp (2016).

75. FAO. Producer prices. (2021). [Accessed at http://www.fao.org/faostat/en/#data/PP]