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# Can technology mitigate the environmental impact of dairy farms?

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ABSTRACT

The aim of the study was to evaluate the effect of the adoption of precision technologies in dairy cattle farms on environmental impact of milk production, estimated using the Life Cycle Assessment methodology. Primary data were collected from five dairy farms. Based on this information, scenarios were created to evaluate the effect of introducing an Automated Milking System (AMS) and adopting technologies for udder health monitoring and heat detection. Comparisons among scenarios showed that the application of these technologies helps to reduce the environmental impact of milk production at the farm level. The introduction of the AMS resulted in a mitigation of 1.2–5.8% of Global Warming Potential (GWP) per kg Fat and Protein Corrected Milk (FPCM). The implementation of technological systems for udder health monitoring led to a decrease in GWP per kg FPCM of 0.06–0.04% for every 5% increase in the detection of infected cows. The use of automatic systems for heat detection reduced GWP of 1 kg of FPCM by 9.4%, Acidification by more than 10% and Land use 5.65–7.69%. The effectiveness of precision technologies on environmental impact mitigation depends not only on their implementation and reliability but also on how the information provided is used by farmer.

## 1. Introduction

Increasing farm efficiency and optimizing resource use are effective mitigation strategies for reducing the environmental impact in dairy farming (Gerber et al., 2013; Bava et al., 2014).

Increasing individual milk production and efficiency, along with improving fertility and animal health provide an important contribution to the environmental impact mitigation, by reducing emissions and non-renewable resource use per unit of product (Gerber et al., 2011; Guerci et al., 2013; Bell et al., 2015; Tullo et al., 2019). Garnsworthy (2004) suggested that by optimizing cow fertility, it is possible to reduce methane and ammonia emissions per kg of milk by more than 20%. Health, welfare, and longevity significantly affect the amount of GHGs emitted per kg of milk produced, by influencing cow productivity, feed conversion and fertility (Vellinga and De Vries, 2018; Mostert et al., 2019; von Soosten et al., 2020). It is estimated, indeed, that diseases can reduce the livestock productivity by 25% (von Soosten et al., 2020). In particular, some studies have focused on the increase in environmental impact due to the onset of mastitis, one of the most important diseases in dairy cattle (Hospido and Sonesson, 2005; Mostert et al., 2019). The greater environmental impact was attributed to the increased risk of early culling of cows, reduced milk production, discarded milk, and extended calving interval. Gülzari et al. (2018) estimated a 3.7% reduction in GHG emissions per kilogram of corrected milk with a decrease in somatic cell count from 800,000 to 50,000 cells per ml.

In addition, good health can increase the lifespan of cows, resulting in environmental benefits due to the reduction in unproductive periods compared to productive periods. Von Soosten et al. (2020) reported in a model that cows reaching 5–8 lactations reduce their emissions per kg of milk by approximately 40% compared to cows culled after the first lactation. Similarly, Vellinga and De Vries (2018) showed that increasing lifespan from 2 to 6 years reduces GHG emissions by 14–19% per kg of fat and protein corrected milk (FPCM).

The goodwill and skills of the farmer are essential for improving herd efficiency, but are they sufficient to tackle the challenge of reducing the impact of livestock farming? At the European level, a new target has been set, namely, to halve GHG emissions by 2030 (Euco, 2020). Therefore, it is crucial to study all the available strategies to improve farm management for reducing the environmental impact of livestock. One potential solution is the adoption of Precision Livestock Farming (PLF) technologies that can assist farmers in identifying herd issues and improving livestock efficiency (Niloofar et al., 2021). In fact, Lovarelli et al. (2020) reported that PLF could mitigate the environmental impact of livestock farming by optimizing input utilization on the farm and

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reducing production risks. However, to the best of our knowledge, there are few studies in the scientific literature that have utilized the life cycle assessment (LCA) methodology to evaluate the environmental effects, on different environmental impact categories, derived from PLF implementation at farm level (e.g., Balaine et al., 2020; Pardo et al., 2022). Lovarelli et al. (2023) considered the effects of some PLF technologies at cow dairy farm level on GWP, not including other environmental impacts categories.

This study aims to investigate whether and how PLF technologies, if smartly and carefully applied, can help to reduce environmental impact of milk production. The analyses were performed using data from actual farms, and the effect of the implementation of different technologies was studied. In particular, the present work focused on how the implementation of automatic milking systems (AMS) and the application of smart technologies for monitoring fertility and udder health can enhance herd efficiency and mitigate the environmental impact of milk production. The present study is one of the first, in the Italian and European context, where environmental evaluation of the introduction of technologies in dairy farms was performed, analysing different environmental impact categories, through the life cycle assessment (LCA) methodology. As far as we know, it is the first time that the introduction of AMS and PLF sensors for udder health evaluation were evaluated thought LCA.

## 2. Materials and methods

Five dairy cattle farms from Lombardy (Italy) were involved in the study. Table 1 provides information about the farms, including details about the herds and the technologies implemented, with reference to the years 2019 (E farm) and 2020 (A, B, C and D farms). Information about animal diets and the use of fertilizers are reported in Table S1.

Farm technological level was calculated using two different scores: diffusion rate score and adoption time score. The diffusion rate score refers to the presence of precision instruments on the farm (no = 0; yes = 1), while the adoption time score considers the time elapsed since adoption, with scores ranging from 1 (adoption for less than 1 year) to 5 (adoption for more than 5 years). Further details about the scores are reported by Bianchi et al. (2022). These technological scores provide information about the technology level of farms and the period of implementation of technologies at the farms.

### 2.1. Life cycle assessment

The evaluation of the environmental impact of milk production was performed through the life cycle assessment (LCA) methodology, following ISO 14040-compliant and ISO 14044-compliant LCA methodology (ISO 2006a; ISO 2006b). The LCA analysis was based on data obtained from the five dairy cattle farms, with reference to the years 2019 (E farm) and 2020 (A, B, C, and D farms).

The goal of this LCA study was to quantify the GWP, Acidification, Eutrophication (freshwater and marine), Land use and Resource use (fossils) of milk production and to evaluate the role of technology implemented on farms as a strategy for mitigating emissions.

### 2.2. Functional unit, system boundaries and allocation procedure

The 6 farms produced raw milk to sell to companies, so the functional unit considered was 1 kg of Fat and Protein Corrected Milk (FPCM) with a composition of 4.0% fat and 3.3% protein following the guideline reported by IDF (2015) for milk at farm level without transformation. The allocation between milk and meat was performed using the biophysical allocation method recommended by the International Dairy Federation using the formula Allocation Factor of milk = 1–6.04 x BMR, (con BMR = Mass meat/Mass milk) (IDF, 2015), with the average allocation factor for milk being 85.8 ± 6.8%. In the scenario analyses reported below, the allocation between milk and meat was adjusted based on variations in milk production levels and/or different culling rates.

The system boundaries considered included the processes from cradle to farm gate. All the inputs (e.g., off-farm feed, bedding material, machinery, fuel, electricity, fertilizers and pesticides) and outputs (e.g., emissions to the air, milk and meat) throughout the production processes were considered (Fig. 1).

### 2.3. Life cycle inventory

Primary data, which was collected through face-to-face questionnaires during farm visits, formed the basis of the study. These data encompassed information about cropping system, herd composition, manure management, feeding rations, purchased forages, concentrates and mineral-vitamin integration, milk production and composition. Additionally, secondary data from the Ecoinvent V3.8 2021 and Agri-footprint (V6, 2022), databases, which are the main databases in terms of environmental impact evaluation of animal feed and animal production, were used.

At the barn level, all the emissions related to milk production were calculated. The methane emissions from enteric fermentation were estimated for all livestock categories by using the equations of the Intergovernmental Panel on Climate Change (Equation 10.19 and Equation 10.21, IPCC, 2019a). The methane emissions from manure storage were estimated using Equation 10.23 of the IPCC (2019a) Tier 2 method. Volatile solid excretion was estimated considering the gross energy of the diets (kJ/kg of dry matter) by using Equation 10.24 of the IPCC (2019a). For the feed digestibility, values suggested by Product Category Rules of Grana Padano PDO (Protected Designation of Origin) were used. $N_2O$ emissions from manure storage occurred in direct and indirect forms, and they were estimated using Equation 10.25 and Equation 10.28 from IPCC (2019a) for direct and indirect emissions, respectively. In the current study, animal nitrogen excretion was estimated as proposed by the IPCC (2019a) Tier 2 method, considering the nitrogen intake (on the basis of the crude protein % of the diet) minus the nitrogen retained by the animals and excreted with milk (Equation 10.31A, option 2). The effects on direct and indirect $N_2O$ emissions derived by the application on the field of organic (solid and slurry) and synthetic fertilizers, as well as crop residues, were accounted for using Equation 11.2 and Equation 11.9 for direct and indirect emissions, respectively (IPCC 2019b). $NH_3$ from housing and manure storage was estimated through the European Environment Agency method (EEA, 2019a), as well as $NO_2$ from manure storage.

$NH_3$ from manure and chemical fertilisers spreading was accounted for, using the European Environment Agency method (EEA, 2019a,b), as

**Table 1**
Data of farms involved in the study with reference to the years 2019 (E farm) and 2020 (A, B, C and D farms).

| farm | lactating cows (n) | milk/cow/day (kg) | milking system | automatic heat detection systems | Year of technology adoption | age at first calving (month) |
|---|---|---|---|---|---|---|
| A | 500 | 37.7 | milking parlor | activometers | 2005 | 23.5 |
| B | 40 | 25.6 | pipeline | none | / | 26.0 |
| C | 106 | 33.8 | milking parlor | activometers | 2012 | 24.7 |
| D | 500 | 37.0 | automatic milking system | activometers | 1999 | 24.0 |
| E | 100 | 27.0 | milking parlor | milk progesterone detection | 2010 | 26.4 |

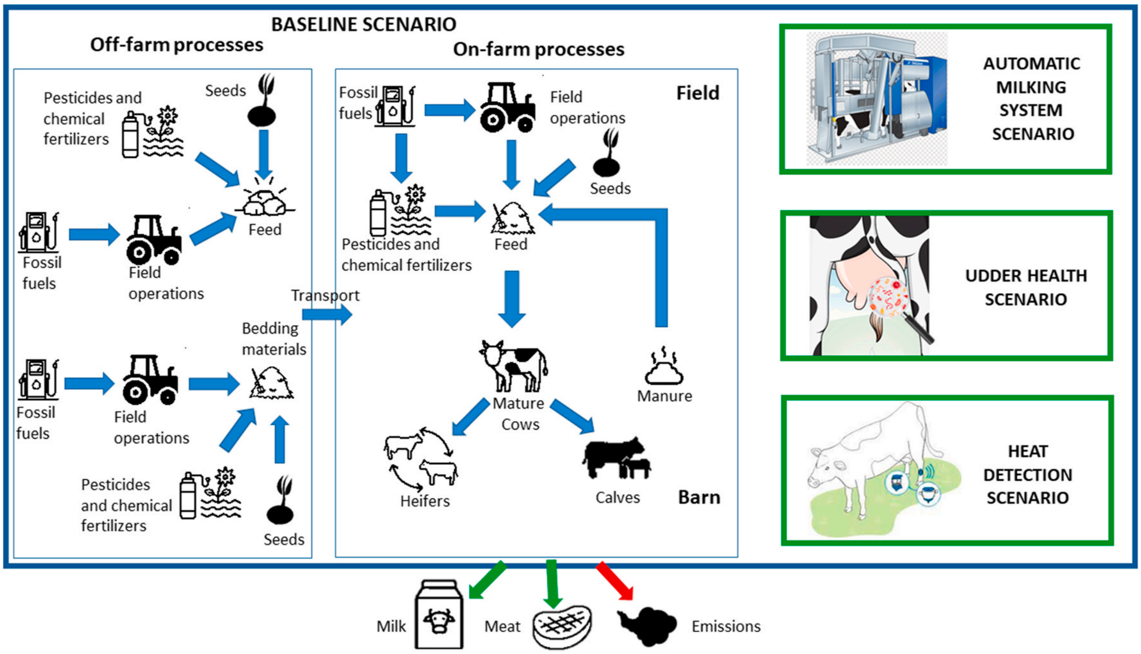


**Fig. 1.** The system boundaries from cradle to farm gate.

well as $NO_2$ from chemical fertilisers spread in the field (EEA, 2019a). $PO_4$ and $NO_3$ emissions resulting from organic and inorganic fertilisers were computed as proposed by Nemecek and Kägi (2007) and IPCC 2019b for $PO_4$ and $NO_3$, respectively.

For soybean meal and oil, direct land use change (LUC) was included in the assessment. Different LUC methods result in significantly different outputs; in this study, Agri-footprint (V6, 2022) database was used. According to the database, the impact for soybean meal (solvent) at processing is 4.30 kg of $CO_2$ eq/kg for Brazilian soybean meal and 1.58 kg of $CO_2$eq/kg for Italian soybean meal. Since, according to ASSALZOO (National Association of Animal Feed Producers, 2018), in Italy, 20% of all purchased soy feeds and derivatives come from Italy and 80% come from South America.

The emissions associated with off-farm activities were calculated using the Ecoinvent V3.8 2021 and Agri-footprint (V6, 2022) databases, implemented in Simapro PhD 9.4.0.2 software. The considered processes included the production chain of commercial feed (from crop growing to feed factory processing), as well as the production of purchased forages and bedding material and the production of synthetic fertilizers, pesticides, diesel, and electricity used on the farms. Transportation emissions were accounted for by materials brought in from outside of the farm.

### 2.4. Life cycle impact assessment

After classification, characterization was performed through Environmental Footprint method (EF 3.0 adapted V1.03), implemented in Simapro software, to evaluate the environmental impact of milk production in terms of GWP (kg of $CO_2$ eq), Acidification (mol H+ eq), Eutrophication (freshwater and marine) (kg P eq and kg N eq), Land use (Pt) and Resource use (fossils) (MJ). Selected impact categories were the most used in studies that applied LCA at dairy farms (Berton et al., 2021; Pardo et al., 2022). Differences between biogenic and fossil methane were taken into account by giving different characterization factors, as required by the method used.

### 2.5. Scenario analyses

#### 2.5.1. Automatic milking system scenarios

In this scenario, the environmental effects of AMS adoption in two of the five dairy farms (Farms B and E) that currently perform parlor or pipeline milking was studied. First, the GWP of the production of 1 kg of FPCM was estimated using the LCA methodology based on the actual farm data (baseline scenario). Then, by simulating changes in some farm indicators (Table 2), as reported in the scientific literature, eight different scenarios were created (Table 3).

An increase in milk fat and protein was applied only in the AMS3, AMS4, AMS7 and AMS8 scenarios, as certain studies reported no

**Table 2**
Changes assumed in Automatic Milking System scenarios.

| Scenario | Indicators | Changes | References |
|---|---|---|---|
| Automatic Milking System | milk yield | increased by 5% increased by 15% | Bernier-Dodier et al. (2010); Hansen (2015); Melin et al. (2005) |
| | milk fat content | increased by 0.10% | Toušová et al. (2014) |
| | milk protein content | increased by 0.06% | |
| | Dry Matter Intake (DMI) | increased in accordance with the increase of milk yield[a] | Allen et al. (2019); Pacchioli et al. (2011) |
| | Purchased feed | increased in accordance with the increase of DMI | |
| | Energy consumption | increased by 1.80 kWh and 2.44 kWh per 100 L of milk | Calcante et al. (2016) |
| | Somatic Cell Count (SCC) | increased by 8.6% | De Koning (2010) |

where FNDF = forage NDF content of diet (% of DM), ADF/NDF = ADF as a fraction of NDF in the ration, FNDFD = digestibility of forage NDF measured in vitro or in situ (% of FNDF), and MY = mean milk yield (kg/d), and assuming FNDF content of 4%.

[a] DMI (kg/d) $= 12.0 - 0.107 \times FNDF + 8.17 \times ADF/NDF + 0.0253 \times FNDFD - 0.328 \times (ADF/NDF - 0.602) \times (FNDFD - 48.3) + 0.225 \times MY + 0.00390 \times (FNDFD - 48.3) \times (MY - 33.1)$.

**Table 3**
Details of changes applied in the eight different Automatic Milking System scenarios.

| Scenario | Milk Yield | Milk Fat and Protein Content | Dry Matter Intake (DMI) | Feed Purchase | Energy Consumption (for 100 L of milk) |
|---|---|---|---|---|---|
| AMS1 | +5% | No | Yes | yes | +1.8 kWh |
| AMS2 | +5% | No | Yes | yes | +2.44 kWh |
| AMS3 | +5% | yes | yes | yes | +1.8 kWh |
| AMS4 | +5% | yes | yes | yes | +2.44 kWh |
| AMS5 | +15% | no | yes | yes | +1.8 kWh |
| AMS6 | +15% | no | yes | yes | +2.44 kWh |
| AMS7 | +15% | yes | yes | yes | +1.8 kWh |
| AMS8 | +15% | yes | yes | yes | +2.44 kWh |

changes in milk composition following the introduction of AMS (Hovinen and Pyörälä, 2011).

Subsequently, all scenarios were simulated with an 8.6% increase in Somatic Cell Count (SCC) due to the introduction of AMS, as reported in Table 2. The aim was to compare these scenarios with the 8 AMS scenarios and to evaluate, even in the case of a worsening SCC, whether AMS adoption is still a valid environmental mitigation strategy.

In these scenarios (8 AMS with an increased SCC), worsening udder health, resulting in a higher percentage of cows prone to mastitis (Hovinen et al., 2009), an increase in discarded milk and in the number of animals to replace, as well as a decrease of 150 kg of milk per mastitis case (>200,000 cells/ml), was considered (Adriaens et al., 2021).

An impact assessment regarding the energy consumption of the entire production process introducing AMS was also made. The differences between scenarios with a minimum consumption of energy (1.80 kWh per 100 L of milk; AMS1 AMS3 AMS5 and AMS7) and scenarios with a maximum consumption (2.44 kWh per 100 L of milk; AMS2 AMS4 AMS6 and AMS8) were thus compared (Calcante et al., 2016). Amounts of FPCM sold by the two farms in different AMS scenarios were reported in Table S2.

### 2.5.2. Udder health scenario

To evaluate the environmental effects of the implementation of precision technologies for monitoring mastitis risk, an Udder Health (UH) scenario was created starting from actual data of two farms (Farms A and D). Considering that both farms normally monitor electrical conductivity and milk flow to detect mastitis, in the UH scenario, the lack of mastitis detection instruments was assumed, resulting in a lower detection capacity than the actual capacity. As reported by Hogeveen et al. (2010), mastitis detection sensors, such as instruments for monitoring electrical conductivity, have a sensitivity of approximately 80%; thus, in the UH scenario, considering a 5% lower ability to detect mastitis, a sensitivity of 75% was envisaged. The correct use by breeders of the information provided by technological instruments was taken for granted.

In the UH scenario, it was assumed that a greater number of cows with mastitis were not identified by farmers and, consequently, were not treated (Table 4).

In this scenario, a variation in purchased feed was considered due to the variation in the number of cows and heifers in the herd. On the other hand, a decrease in dry matter intake (DMI) in cows with mastitis was not considered important and, therefore, was not estimated.

The increase in untreated mastitis cases was expected to result in an increase in milk SCC affecting the amount of discarded milk (DisM), that is, milk not sold due to the presence of antibiotics or high SCC. Therefore, the environmental consequences of DisM were also evaluated.

For the UH scenario, a sensitivity analysis was performed using 2 different levels of milk reduction in the case of mastitis suggested by Adriaens et al. (2021) and Seegers et al. (2003), namely, losses of 150 and 300 kg of milk per lactation for each case of mastitis.

#### 2.5.2.1. Effects on the environmental impact of discarded milk.

One of the benefits resulting from better udder health monitoring is the reduction of DisM. To explore the role of this change in decreasing the environmental impact of milk production, estimations were made on the amount of DisM in two dairy farms (Farms A and D). First, the actual DisM quantity was calculated for the period between 2016 and 2021 by subtracting the milk sold and, if applicable, the milk used for calf feeding, as declared by farmers, from the total milk produced. The total milk produced was obtained using the monthly official controls of the National Breeders Association.

Second, the environmental effects of reduced DisM were evaluated, hypothesizing a reduction of 1 kg of discarded FPCM head/day in 4 different years: 2016, 2019, 2020 and 2021.

An evaluation using the LCA methodology was conducted considering the change in milk production per year, obtained by the reduction of DisM. Then, the GWP estimated was compared with the GWP assessed in the same farms, considering the real milk yield without the reduction of DisM.

### 2.5.3. Heat detection scenario

Real data from two Lombardy dairy farms (Farms C and E) using different heat detection tools were considered to build an LCA scenario (HD) analysis that aimed to evaluate the environmental effects of technology for managing reproduction. In particular, one farm used activometers, while the other farm had sensors to detect milk progesterone.

Age at first calving and calving interval were considered indicators of reproductive performance for both herds. Differences in these variables were measured before and after the introduction of a heat detection automatic system. For both farms, 2008 was considered the reference year before the introduction of these instruments, while for the period after the adoption of these instruments, 2020 was taken as a reference. A General Linear Model (GLM) was performed using the SAS statistics program (SAS, 2012) to verify whether there were significant differences in reproductive performance over time. The model used was as follows:

**Table 4**
Changes assumed in Udder Health scenario.

| Scenario | Indicators | Changes | References or calculation way |
|---|---|---|---|
| Udder Health scenario | cows with mastitis not identified by farmer | increased by 5% | Hogeveen et al. (2010) |
| | cows with at least 4 official milk controls with 400,000 cells/ml or more, and then culled | increased by 5% | |
| | milk yield | reduced by 150 kg/lactating cow with mastitis not identified | Adriaens et al. (2021) |
| | lost milk of culled cows | Fat and Protein Corrected Milk (FPCM) produced (kg/cow/year) * number of extra cows culled with high SCC (400,000 cells/ml) | according to the number of infected cows not identified by farmer and then culled |
| | number of heifers | increased by 11.7% | according to the replacement of culled cows |
| | purchased feed | decreased by 2.28% | according to the different number of cows (decreased due to culled cows) |
| | | increased by 0.83% | according to the different number of heifers (increased due to replacement of cows) |

$$Y_{ijkl} = \mu + T_i + F_j + Sk + TF_{ij} + S_k + e_{ijkl}$$

where $Y_{ijkl}$ represents the dependent variables (age at first calving and calving interval), $\boldsymbol{\mu}$ is the general mean, $T_i$ is the effect of introduction of technology for heat detection (i = before and after), $F_j$ is the farm effect (j = C and E); $S_k$ is the effect of calving season (k = cold and hot season); $TF_{ij}$ is interaction effect; and $e_{ijkl}$ is the residual error.

To test the calving interval, the parity effect ($P_m$) was also included in the model (m = 1–3; primiparous, secondiparous, multiparous).

Whenever possible, actual farm data were used to obtain simulations that closely resembled reality. In the HD scenario, changes in indicators were made using the starting data for 2020, taking into account the differences in reproductive performance over time (2008–2020) (Table 5).

The reduction of DMI, as a result of lower milk production during cow lifespan, was considered; however, changes in the DMI of primiparous cows due to delay in first calving and lengthening of the unproductive period, were not considered (Grummer et al., 2004).

A reduction in milk yield was considered both due to the reduced age at first calving and the shorter calving interval.

A Monte Carlo simulation was performed for all scenarios to assess the extent to which uncertainties associated with the data used in the study can influence the observed environmental impacts. The analysis was conducted with a 95% confidence interval and 1000 iterations.

## 3. Results

In Fig. 2, the technological scores (diffusion rate score and adoption time score) and the GWP (kg $CO_2$ eq./kg of FPCM) for each farm are reported.

The mitigation of GWP per kilogram of milk achieved through the introduction of AMS ranged from 1.20% to 5.83% (Table 6). The results on Acidification, Eutrophication (freshwater and marine), Land use and Resource use, environmental impact categories are reported in Table 7. The least-mitigating scenarios were those with the highest energy consumption and the lowest milk production improvement (AMS2 and AMS4). In particular, for energy use category, the effect was very low in farm B and negative in farm E, with an increase in this category by 2.5%. The greatest environmental benefits, in particular for Eutrophication (freshwater and marine) (0.0002 and 0.0002 kg P eq. and 0.009 and 0.007 kg N eq. for freshwater and marine in baseline scenario for B and E farms, respectively) and Land use (100.6 and 70.0 Pt in baseline scenario, for B and E farms, respectively) were associated with the AMS5 and AMS7 scenarios, characterized by the highest increase in milk production (+15%) and the lowest energy consumption. Considering only energy consumption, the increase only led to a GWP worsening from 0.16% (Farm E) to 0.06% (Farm B), while the improvement in milk quality, in terms of fat and protein content, produced an average environmental benefit of 0.05%. The main driver was the increase in milk yield.

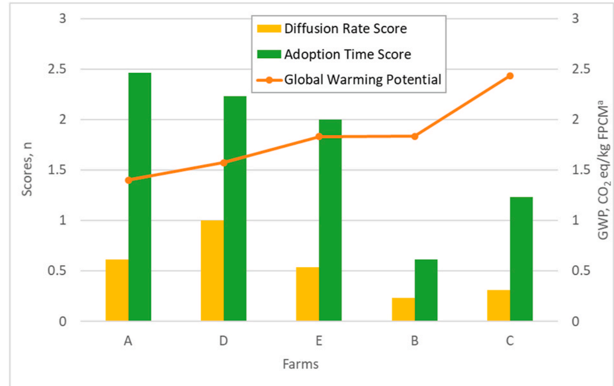


**Fig. 2.** Diffusion Rate Score, Adoption Time Score and Global Warming Potential of milk production in the five Italian dairy farms involved in the study. [1]FPCM = Fat and Protein Corrected Milk.

**Table 6**
Global Warming Potential of B and E farms' AMS scenarios.

| | B farm | | E farm | |
|---|---|---|---|---|
| Scenario | kg $CO_2$ eq./ kg of Fat and Protein Corrected Milk | decrease in Global Warming Potential compared to the baseline scenario (%) | kg $CO_2$ eq./ kg of Fat and Protein Corrected Milk | decrease in Global Warming Potential compared to the baseline scenario (%) |
| baseline | 1.7313 | _ | 1.8690 | _ |
| AMS1 | 1.6997 | 1.86 | 1.8447 | 1.36 |
| AMS2 | 1.7008 | 1.79 | 1.8477 | 1.20 |
| AMS3 | 1.6991 | 1.89 | 1.8435 | 1.42 |
| AMS4 | 1.7001 | 1.83 | 1.8465 | 1.27 |
| AMS5 | 1.6316 | 5.79 | 1.7849 | 4.56 |
| AMS6 | 1.6326 | 5.73 | 1.7876 | 4.41 |
| AMS7 | 1.6308 | 5.83 | 1.7837 | 4.62 |
| AMS8 | 1.6318 | 5.78 | 1.7864 | 4.47 |

The increase in SCC due to the introduction of AMS resulted in a modest increase in GWP per kg of FPCM ranging between 0.03% and 0.06% compared to the AMS scenarios. In fact, the GWP of milk in the farms in which the adoption of AMS led to an increase in SCC was still 1.1% (Farm E) and 1.8% (Farm B) lower than the impact values of the baseline scenarios. This percentage was calculated taking into consideration the AMS2 scenario (i.e., the worst one, with a 5% increase in milk production, a maximum energy consumption and a fat and protein content unchanged) compared to the baseline scenario; of course, considering the other scenarios, the difference between the AMS and the baseline scenarios was greater.

Regarding the UH scenario, a decrease in mastitis detection capacity

**Table 5**
Changes in Heat Detection scenario.

| Scenario | Indicators | Changes | References or calculation way |
|---|---|---|---|
| Heat Detection | days in milk | increased by almost 14.9% | from the difference in calving interval over the years considering the same number of cows |
| | milk yield | reduced by 4.10% | from the extra non-productive months*primiparous (n.)*average milk produced/cow/day |
| | | reduced by 4.10% | due to the increase in days in milk - Lehmann et al. (2019) |
| | DMI | reduced by 7.10% | Lehmann et al. (2019) |
| | purchased feed | reduced in accordance with DMI reduction | Lehmann et al. (2019) |
| | number of lactating cows | increased by about 10% | in accordance with longer lactations |
| | dead cows | increased by 16.3% | in accordance with the increase of lactating cows |
| | sold cows | reduced by 49.9% | |
| | age at first calving | increased by 1.2–1.6 months | from the difference in age at first calving over the years |

**Table 7**
Percentage variations between baseline and Automatic Milking System scenarios, for the considered environmental impact categories.

| Farm | Impact category | AMS1 | AMS2 | AMS3 | AMS4 | AMS5 | AMS6 | AMS7 | AMS8 |
|---|---|---|---|---|---|---|---|---|---|
| B farm | Acidification | −1.96 | −1.93 | −2.03 | −2.00 | −5.95 | −5.92 | −6.03 | −6.01 |
| B farm | Eutrophication, freshwater | −1.74 | −1.37 | −1.77 | −1.40 | −7.29 | −6.94 | −7.33 | −6.98 |
| B farm | Eutrophication, marine | −2.62 | −2.61 | −2.66 | −2.65 | −7.72 | −7.70 | −7.78 | −7.77 |
| B farm | Land use | −2.80 | −2.77 | −2.84 | −2.81 | −8.42 | −8.40 | −8.47 | −8.44 |
| B farm | Resource use, fossils | −1.71 | −1.25 | −1.75 | −1.29 | −7.59 | −7.16 | −7.64 | −7.20 |
| E farm | Acidification | −1.74 | −1.68 | −1.82 | −1.76 | −5.25 | −5.19 | −5.33 | −5.28 |
| E farm | Eutrophication, freshwater | −1.06 | −0.53 | −1.12 | −0.59 | −6.03 | −5.53 | −6.09 | −5.59 |
| E farm | Eutrophication, marine | −2.39 | −2.36 | −2.46 | −2.43 | −7.07 | −7.04 | −7.13 | −7.10 |
| E farm | Land use | −2.76 | −2.76 | −2.83 | −2.82 | −8.10 | −8.09 | −8.16 | −8.15 |
| E farm | Resource use, fossils | 1.05 | 2.53 | 0.98 | 2.46 | −4.70 | −3.31 | −4.76 | −3.37 |

due to the lack of a technological system (SCC and electrical conductivity monitoring) for udder health monitoring at the farm produced an increase in GWP and other considered environmental impact categories between 0.06% and 0.04% for every 5% decrease in infected cows detected, in comparison with the baseline scenario. A different benefit of using an udder health monitoring technology was noted in Farms A and D, where this scenario was applied. The SCC situation of the two farms was initially different; in Farm A, 14% of the cows achieved more than 4 monthly official controls of the National Breeders Association with high SCC (more than 400,000 cells/ml), while in Farm D, the percentage was lower (5%).

As a consequence of the increased number of culled cows, GWP increased by 0.80% in the first farm (A) and 0.08% in the second farm (D). Also for acidification, eutrophication, land use and resource use, the environmental benefits in farm D were minimal and even negative for marine eutrophication and acidification. Results of other environmental categories are reported in Table 8.

The increase in the GWP was 1.31% (Farm A) and 0.31% (Farm D) if only the quantity of lost milk due to SCC raising was considered. On the other hand, considering only the herd changes (fewer lactating cows and more heifers), the increase in the GWP was lower, i.e., 0.77% (Farm A) and 0.04% (Farm D). The results from sensitivity analysis based on reduced milk production due to mastitis reported a reduction in GWP of 0.13% for Farm B.

Regarding the quantification of DisM over the years, as expected, an average decrease was recorded for farms A and D: on average, in 2016, 4.60 ± 1.18 kg of milk/cow per day was discarded, while in 2021, approximately 2.74 ± 0.51 kg of milk was discarded (in 2019 and 2020, on average, 3.24 ± 1.24 and 2.74 ± 2.25 kg of milk/cow per day was discarded, respectively). Analysing the environmental benefit of the DisM reduction, it was found that the reduction of only 1 kg of discarded FPCM head/day leads to an average reduction in GWP of approximately 2.6%, considering different years (2016, 2019, 2020 and 2021).

Regarding the reproductive scenario, the calving interval was 447 ± 3.69 days before the introduction of automatic heat detection systems and 400 ± 3.00 days after the introduction of automatic heat detection systems. Considering age at first calving, averages of 27.0 ± 0.16 and 25.7 ± 0.11 months were obtained before and after the technological investment, respectively. The GLM confirmed an improvement over time in the reproductive performances of Farms C and E before and after the introduction of automatic heat detection systems (activometers and sensors for progesterone detection).

The introduction of these technologies led to a reduction in all the assessed environmental categories, notably Acidification (10.6%) and GWP (9.4%). When farmers monitored the heat only visually, the impact of 1 kg of FPCM was 9.4 ± 0.5% higher than the GWP found in the scenario using automatic heat detection systems. The results about environmental categories are reported in Table 9.

The comparison of average mitigation effects for the use of different technologies is reported in Fig. 3. Regarding the udder health scenario, a 5% lower ability to detect mastitis was considered, reaching 80% sensitivity.

The uncertainty analysis confirmed that the GWP evaluated using data from farms that use PLF tools was always lower than the estimation obtained without the use of PLF.

## 4. Discussion

The average milk yield of the five farms could be assumed to be representative of dairy farms in Lombardy, which have, on average, a slightly lower milk yield compared to their counterparts (−3.5%; AIA, 2020). The reproductive performance (age at first calving) of the studied farms was 7.7% better than the regional average (AIA, 2020). Considering the diffusion rate score and adoption time score of the technologies implemented on the farms, both were higher than the values reported by Bianchi et al. (2022), indicating a good level of technological advancement in the studied farms. However, high variability between farms was noticed for both the diffusion rate score (0.539 ± 0.30) and the adoption time score (1.71 ± 0.766).

The results regarding the LCA of each farm indicate that the GWP and Acidification of the involved farms had values included between the minimum and maximum values described by Gislon et al. (2020), who reported an average GWP and Acidification for milk production of approximately 1.37 kg of $CO_2$ eq./kg of FPCM and around 0.03 mol $H^+$ eq respectively. Although not statistically proven, due to the limited number of farms, the highest GHG emissions per kilogram of milk were observed in farms characterized by a lower technological level compared to the others (Farms B, C and E), specifically, lower diffusion rate scores and adoption time scores.

From the results obtained in the scenario analysis regarding the introduction of AMS in dairy farms, the environmental benefit of

**Table 8**
Percentage variations between baseline and Udder Health scenario, for the considered environmental impact categories.

| Impact category | A farm | D farm |
|---|---|---|
| Global Warming Potential | 0.80% | 0.08% |
| Acidification | 0.65% | −0.18% |
| Eutrophication, freshwater | 0.96% | −0.03% |
| Eutrophication, marine | 1.04% | 0.11% |
| Land use | 1.09% | 0.24% |
| Resource use, fossils | 1.10% | 0.10% |

**Table 9**
Increase (%) in heat detection scenario without technologies in C and E farms'

| Impact category | Increase (%) | |
|---|---|---|
| | C farm | E farm |
| Global Warming Potential | 9.78% | 9.04% |
| Acidification | 10.78% | 10.34% |
| Eutrophication, freshwater | 7.95% | 6.20% |
| Eutrophication, marine | 9.13% | 8.09% |
| Land use | 7.69% | 5.65% |
| Resource use, fossils | 7.02% | 5.66% |

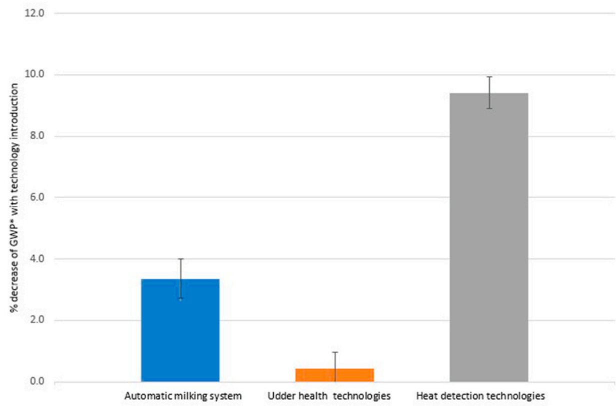


**Fig. 3.** Average mitigation effects for the use of different technologies at dairy farm.
[1]GWP = Global Warming Potential.

adopting this technology is evident on GWP, Acidification, Eutrophication (Freshwater and Marine) and Land Use. The increase in milking frequency drove an increase in milk production. As reported by other authors (Gerber et al., 2011; Guerci et al., 2013) and observed in the present work, increasing the milk production level can reduce the environmental impact per unit of product. At the same time, the results for Resource Use differ between farm B and farm E. In farm E the modest increase in FPCM production (+5%) does not compensate for the higher demand of electricity. Conversely, the main environmental and economic issues associated to the adoption of an AMS can be related to health problems (mastitis or others) due to the less frequent checking of the animals by operators.

For example, Piwczyński et al. (2021) observed that introducing AMS into herds involves increases in the culling rate for locomotor diseases, low milk yield and other health problems; on the other hand, in the same study, it was also observed that milking automation reduced culling associated with udder diseases, as well as with low fertility, accidents and random events. In fact, as stated by Inzaghi et al. (2021), certain information provided by AMS can lead to the early detection of udder health issues. As also reported by other authors (Berglund et al., 2002; Kolenda et al., 2021), SCC can decrease the use of AMS. From an environmental perspective, a decrease in SCC can drive various benefits in addition to economic profits (Gülzari et al., 2018), namely, less milk discarded and extended cow lifespan (Rostellato et al., 2022), due to a lower culling rate for mastitis. However, in contrast, other authors (de Koning, 2010; Hovinen and Pyörälä, 2011) have reported an increase in SCC in milk after the adoption of AMS. This is an undesirable effect that requires further investigation. However, it is important to note that in our scenarios, this increase in SCC did not significantly affect the environmental impact of milk production.

Previous studies (Hospido and Sonesson, 2005; Gülzari et al., 2018; Mostert et al., 2019) have highlighted the influence of mastitis on the environmental impact and, as a consequence, the environmental benefit of improving mastitis detection leading to a lower number of cows culled for this reason. Furthermore, mastitis reduces milk production and quality and contributes to the increase in discarded milk, which are additional factors that have a negative impact on environmental impact of milk production.

The present study has highlighted a reduction in greenhouse gas emissions (expressed ad GWP), land use, and resource utilization resulting from improved mastitis detection in both farms studied, characterized by different initial management practices. Conversely, the effects on acidification and eutrophication varied between the two farms. In fact, in Farm A, the benefits were limited, whereas in Farm D, they were negative. The low values of acidification and eutrophication of freshwater in the scenario without technologies could be attributed to the different ratio of adult to replacement animals, favouring the latter, due to the high replacement rate and the consequent lower nitrogen excretion. Reed et al. (2015) reported lower nitrogen concentration in the diets and excretion of replacement animals compared to lactating cows. The environmental benefit of improved mastitis detection thus differed between the two farms, suggesting, among other things, that the enhancement of environmental sustainability is greater when the initial situation is more critical. Moreover, the changes in herd composition in the scenario with high SCC (and high replacement rate) resulted in a lower GWP per kg of milk due to the lower environmental load (related to enteric emissions and feed purchase) of heifers, in absolute terms, compared to adult cows. However, when considering reduced milk (and discarded milk), high milk SCC still led to higher GWP for milk production at the farm level. In particular, in the case of milk intended for cheese-making, the comparison could be more interesting by also considering subclinical mastitis that can result in lower milk production and dairy efficiency and reduced milk quality (Bonestroo et al., 2022). Subclinical mastitis does not manifest clinically with symptoms; for this reason, it would be more easily detectable using technological tools than visual evaluation.

The amount of discarded milk still represents a significant portion in some farms, which, of course, has implications for the environmental impact per kg of FPCM, but over the other years, a reduction in discarded milk has been observed, which could indicate an improvement in farm management. Among these improvements, the use of technology could also be included.

The large presence of heat detecting systems, not only in Italy (Borchers and Bewley, 2015), underlines how even farmers are aware of the importance of fertility management for the sustainability, especially the economic sustainability, of their farms. Because good fertility has a positive influence on farm efficiency and also on environmental impact of milk, as reported by other studies (Garnsworthy, 2004; Tullo et al., 2019). The scenarios proposed in the present study show that improving reproductive performance can lead to a reduction in all impact categories associated with milk production; this improvement can also be achieved through the use of technological tools.

Regarding the improvement in reproductive performance over time found in this study, it is important to note that it could be due to many factors, such as genetic improvement and good feeding management. However, technology certainly has also played an important role in making dairy farms more efficient in reproductive management. It has been shown that detecting heat with sensors, compared to visual observation, often increases the effectiveness of breeding (Mayo et al., 2019). The use of activity metres leads to a decrease in the average calving interval and consequently to an increase in annual milk production (Rutten et al., 2014). Automated activity monitoring systems reduce labour costs (Stevenson et al., 2014), and investing in these tools for oestrus detection is likely to be profitable for most dairy farms (Rutten et al., 2014).

A comparison among scenarios showed that the application of technologies helps to reduce the environmental impact of milk production at the farm level. The environmental benefits achievable through the implementation of technology on the farm may not appear very meaningful individually, but they can be combined with an additive and possibly synergistic effect. In a study that focused on intensive goat farming, Pardo et al. (2022) showed that after the implementation of a PLF platform, significant reductions (−11%) in greenhouse gases and similar trends in other impact categories emerged. It should also be emphasized that precision technologies can also have social and economic benefits, although these aspects were not evaluated in the present study. Balaine et al. (2020) demonstrated that although the implementation of production and milk quality recordings had no significant impact on the environmental footprint, technology enhanced the economic and social sustainability of milk production. Despite the promising results of the current study on reducing the impact of milk production with the help of technology, it should be remembered that dairy cattle farms produce not only milk but also beef as male calves and culled cows; the effect of mitigation strategies should also be evaluated by taking into account the effects on the beef sector using a system expansion analysis. Improved dairy cow longevity may lead to lower availability of beef from dairy farms, which should be compensated for by increased beef production from pure beef systems; however, such changes also produce impacts. Therefore, it is necessary to provide more extensive insights into the impacts on related production systems.

While the present study has some limitations, notably the utilization of literature-based data for scenario formulation, it has unveiled certain novel aspects that can enhance scientific knowledge in these topics. Moreover, this study did not take into account the economic dimension of introducing new technologies in dairy farms, along with the associated advantages and disadvantages. These economic aspects cannot be overlooked in a comprehensive assessment of sustainability.

## 5. Conclusion

The application of technologies seems to help reduce the environmental impact of milk production at the farm level, specifically when, as demonstrated in this study, such technologies are adopted to automate milking operations and to manage productive, reproductive and udder health aspects. Precision livestock farming has the potential to improve the efficiency and sustainability of livestock production by reducing waste, improving animal welfare and health, and increasing productivity.

The best results were obtained by introducing AMS or automatic heat detection instruments. At the same time, technologies can also lead to an environmental advantage by helping farmers more accurately diagnose and treat animal health issues, leading to improved animal welfare and reduced costs and treatments. However, technologies cannot be considered a stand-alone impact mitigation tool. Much depends on the conditions in which they are applied and how farmers make use of them. PLF is able to provide much information, but the benefit depends on whether these data are used. The use of technology should not lead to a decline in the quality of the human-animal relationship. This aspect deserves further study in the future, as it could be a critical point from the perspective of social sustainability.

The development of integrated precision systems capable of collecting information on animals in relation to multiple aspects (behaviour, intake, production, location, health and welfare status, etc.) and integrating them could provide farmers with reliable and comprehensive information useful for management decisions, making the collected data more useable for the farmer and increasing the environmental benefit compared to individually employed precision systems.

The results of the current study confirm that the LCA methodology is a useful tool for estimating the environmental impact effect of introducing PLF tools in dairy farms. The introduction of new sensors can bring many changes, which are difficult to measure in real-life situations due to other interfering factors such as climate variation, genetics, and feed composition. Scenario analyses using LCA can overcome these challenges and focus 'solely' on the effects of implementing new technology. Additionally, in scenario development, as shown in the present study, it is possible to simultaneously assess the environmental effect of different intensities of changes.

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## CRediT authorship contribution statement

**Maria Cecilia Bianchi:** Writing – original draft, Validation, Software, Methodology, Data curation, Conceptualization. **Giulia Gislon:** Validation, Software. **Sara Mondini:** Writing – original draft, Visualization, Validation, Software, Investigation, Data curation. **Luciana Bava:** Writing – review & editing, Writing – original draft, Supervision, Data curation. **Alberto Tamburini:** Writing – original draft. **Anna Sandrucci:** Writing – review & editing, Visualization, Supervision, Investigation. **Maddalena Zucali:** Supervision, Software, Methodology, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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## Appendix A. Supplementary data

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