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PRECISION LIVESTOCK FARMING IN CATTLE SYSTEMS: PRODUCTIVITY AND SUSTAINABILITY

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Abstract

Precision Livestock Farming (PLF) is an emerging field at the interface of animal science and agricultural engineering, enabling sensor-based monitoring and data-driven management in cattle production. This review synthesises current evidence on PLF applications in dairy and beef systems, focusing on welfare and behaviour, health surveillance (mastitis), reproduction, body condition assessment, productivity, extensive/pasture-based management, and environmental implications. A qualitative literature review was conducted using peer-reviewed papers retrieved from ScienceDirect, PubMed, Scopus, Web of Science, Frontiers, and Google Scholar. Overall, findings indicate that PLF enhances herd performance by enabling continuous monitoring of behavioural and physiological indicators, supporting earlier detection of subclinical disorders, improved reproductive event identification, and objective phenotyping through automated body weight and body condition scoring. Evidence also suggests improved milk and beef production through increased biological efficiency, optimised grazing allocation in extensive systems, and improved estimation of enteric methane emissions. These insights support the adoption of PLF decision-support tools to optimise feeding, health interventions, and pasture management, thereby increasing productivity and supporting sustainability targets.

Key words*: animal welfare, beef cattle, dairy cattle, precision livestock farming, sensor technologies.*

INTRODUCTION

The global livestock sector is undergoing profound transformations driven by population growth, increasing demand for animal-derived products, rising production costs, labor shortages, and intensified societal concerns regarding animal welfare and environmental sustainability. Within this context, cattle production systems, encompassing both dairy and beef sectors, remain fundamental to global food security and rural economies, while also representing a significant share of agricultural land use and greenhouse gas emissions (Banhazi et al., 2012; Lovarelli et al., 2020). Traditional livestock management approaches, largely based on visual observation and group-level decision-making, are increasingly inadequate in modern farming systems characterized by expanding herd sizes and reduced direct human-animal interaction (Caja et al., 2016; Halachmi et al., 2019). Moreover, evidence from other livestock sectors suggests that production conditions may influence product quality traits, including nutritional and sensory characteristics, highlighting the potential for value-added animal-derived products (Bonneau & Lebret, 2010; Lungu et al., 2024, Zinca et al., 2025).

Technological innovation has been identified as a key pathway for addressing these challenges and improving the resilience and efficiency of livestock production systems. In this regard, Precision Livestock Farming (PLF) has emerged as an innovative management paradigm that aims to support farmers through continuous, automated, and objective monitoring of individual animals (Banhazi et al., 2012; Caja et al., 2016; Kelemen et al., 2016). PLF relies on the integration of sensor

technologies, Internet of Things (IoT) devices, automated data acquisition systems, and advanced data processing techniques to generate real-time information on animal behavior, physiology, production, and environmental interactions (Halachmi et al., 2019; Lovarelli et al., 2020). By shifting management from a group-based to an individual-animal-centered approach, PLF enables earlier detection of deviations from normal biological patterns and facilitates timely, targeted interventions. One of the principal motivations for the development and implementation of PLF technologies is the need to enhance animal health and welfare while maintaining or increasing production efficiency. Continuous monitoring of behavioral and physiological indicators allows for the early identification of health disorders, often before the appearance of clinical signs, thereby reducing disease severity, treatment costs, and productivity losses (Neethirajan, 2017; Halachmi et al., 2019). Furthermore, PLF systems provide objective welfare indicators, supporting improved transparency and compliance with increasing societal and regulatory expectations related to animal well-being (Caja et al., 2016; Lovarelli et al., 2020). These capabilities are particularly relevant in cattle production, where subtle changes in activity, rumination, or social behavior may precede health or welfare impairments.

Beyond animal health and welfare, PLF has been widely recognized for its potential contribution to sustainable cattle management. Optimized feeding strategies, improved reproductive efficiency, and enhanced production monitoring can lead to more efficient use of resources and a reduction in the environmental footprint per unit of output (Halachmi et al., 2019; Lovarelli et al., 2020). The large volumes of data generated by PLF systems also enable evidence-based decision-making and support the evaluation of farm performance from both economic and environmental perspectives (Banhazi et al., 2012; Caja et al., 2016). Consequently, PLF is increasingly viewed as an enabling technology for achieving sustainability objectives within livestock production systems.

Most scientific research and commercial applications of PLF have focused on intensive dairy production systems, where indoor housing and automated milking technologies facilitate sensor deployment and data collection (Halachmi et al., 2019; Lovarelli et al., 2020). In contrast, the adoption of PLF in beef cattle and extensive or semi-extensive systems has progressed more slowly, largely due to challenges related to infrastructure availability, sensor robustness, data transmission, and economic feasibility (Caja et al., 2016; Neethirajan, 2020). Nevertheless, recent studies demonstrate that adapted PLF solutions can be successfully implemented in extensive environments, providing valuable insights into animal health, grazing behavior, and welfare status, and highlighting their relevance beyond intensive dairy systems (Caja et al., 2016; Neethirajan, 2020).

Despite the expanding body of literature, existing studies often address isolated PLF applications or specific production systems, resulting in a fragmented understanding of the overall potential and limitations of precision technologies in cattle farming (Banhazi et al., 2012; Halachmi et al., 2019). Moreover, the rapid pace of technological development necessitates continuous synthesis of current knowledge to identify research gaps, methodological challenges, and future research priorities. An integrated review encompassing both dairy and beef cattle systems, as well as intensive and extensive production contexts, is therefore essential to provide a comprehensive overview of the current state of PLF and its role in sustainable cattle management (Caja et al., 2016; Lovarelli et al., 2020). However, despite these advances, important challenges remain, including variability in system performance under commercial conditions, data integration issues, and limited adoption by farmers due to economic and practical constraints.

The objective of this review is to critically synthesize and evaluate recent scientific literature on Precision Livestock Farming in cattle production systems, including both dairy and beef sectors, with particular emphasis on technological approaches, applications in animal health, welfare, reproduction, and production, and their contribution to sustainable livestock management.

MATERIALS AND METHODS

In order to achieve the objectives of this review, a total of specialised scientific papers focusing on Precision Livestock Farming (PLF) in cattle systems were analysed. The selected literature covered the main PLF application domains in dairy and beef cattle, including welfare and behavioural monitoring, health management (with emphasis on mastitis), reproductive monitoring, body condition assessment, productivity-related outcomes, extensive/pasture-based systems, and environmental implications.

The publications were retrieved from major international scientific databases and platforms, namely ScienceDirect, PubMed, Scopus, Web of Science, Frontiers, and Google Scholar, using relevant keywords and combinations (e.g., precision livestock farming, dairy cattle, beef cattle, sensors, mastitis detection, oestrus detection, GPS monitoring, body condition score, and emissions). The literature search focused primarily on studies published in the last 10-15 years, with emphasis on recent advances in PLF technologies. Following the literature screening, the analysis was conducted through qualitative synthesis, based primarily on observation and thematic grouping. The results were subsequently structured into key sections reflecting the major biological and managerial functions targeted by PLF technologies, thereby providing an integrated overview of their role in improving productivity, welfare, and sustainability in cattle production systems.

RESULTS AND DISCUSSIONS

Welfare and Behaviour Monitoring

Welfare and behaviour monitoring represents one of the most mature and widely applied domains of Precision Livestock Farming (PLF), as behavioural changes frequently precede clinically detectable health disorders and declines in productivity. The analysed literature consistently shows that PLF enables continuous, objective, and individual-level assessment of cattle behaviour, overcoming the subjectivity and limited temporal resolution of conventional welfare evaluation based on periodic visual inspection (Mirzaei et al., 2013; Caja et al., 2016). Core behavioural indicators, including lying, resting, rumination, activity, and vocalisation, are repeatedly identified as reliable proxies of animal welfare across different production systems.

In dairy calves, lying and resting behaviour dominate early life stages and are closely associated with comfort and housing quality, while deviations from expected behavioural patterns are linked to stress and impaired welfare (Pesenti Rossi et al., 2024). In adult dairy cows, reductions in rumination time and alterations in activity patterns were consistently observed during periods of physiological challenge, particularly around parturition, enabling earlier identification of animals at risk compared with traditional monitoring approaches (Mirzaei et al., 2023). These findings underline the value of behavioural metrics as early-warning indicators of compromised welfare.

Wearable sensors, particularly accelerometer- and rumination-based systems, are widely reported as effective tools for behavioural monitoring, providing high temporal resolution and continuous data streams (Mirzaei et al., 2023; Pesenti Rossi et al., 2024). Complementary non-contact approaches further extend PLF capabilities. Acoustic monitoring based on vocalisation analysis demonstrated high accuracy in identifying behaviourally relevant events, suggesting potential applications beyond reproduction, including social behaviour and discomfort detection (Wang et al., 2023). Similarly, computer vision approaches using deep learning models enabled automated recognition of postures and activities without physical contact, offering clear welfare advantages by reducing animal disturbance and device-related constraints (Sim et al., 2024). However, despite these advantages, several studies highlight important limitations of behavioural monitoring systems. Sensor accuracy may be affected by environmental conditions, animal variability, and device placement, leading to inconsistencies in data quality under commercial farm conditions. In addition, wearable devices may require regular maintenance and calibration, which can limit their practical applicability, particularly in

large-scale or extensive systems (Berckmans, 2014).

Although implementation differs between intensive and extensive systems, the overall evidence indicates that PLF substantially improves welfare monitoring in both contexts. Controlled environments in intensive dairy systems facilitate higher accuracy, while in extensive systems PLF enables continuous assessment of activity, grazing behaviour, and spatial distribution that is otherwise difficult to achieve (Caja et al., 2016). Nevertheless, the effectiveness of PLF technologies is not uniform across studies. While some research reports high accuracy and reliability of sensor-based behavioural monitoring, other studies indicate moderate performance, particularly in complex or variable environments, suggesting that system performance is highly context-dependent (Banhazi et al., 2012; Berckmans, 2017). Collectively, the literature converges on the conclusion that PLF-based behavioural monitoring enhances welfare assessment through improved objectivity, earlier detection of welfare-related deviations, and greater capacity for proactive management interventions (Caja et al., 2016). From a practical perspective, these findings suggest that farmers can use PLF systems to monitor animal behaviour more efficiently, detect welfare issues at an early stage, and support timely management decisions, potentially reducing labour requirements and improving overall herd management (Lovarelli et al., 2020).

Health Monitoring: Mastitis Detection

Mastitis is one of the most important diseases affecting dairy cattle, generating substantial economic losses and negatively impacting milk quality, animal welfare and farm sustainability (Stanek et al., 2024). In addition, the microbiological quality of dairy products remains a relevant concern along the production chain, as contamination may affect both product safety and marketability (Şuler et al., 2021). Conventional diagnostic approaches, based on clinical observation and periodic somatic cell count (SCC) measurements, are often reactive and insufficient for early detection, particularly in subclinical cases. Precision Livestock Farming (PLF) technologies provide a data-driven alternative by enabling continuous, automated monitoring of udder health.

A comparative overview of conventional and PLF-based mastitis detection approaches is presented in Table 1.

Table 1. Comparison between conventional and PLF-based mastitis detection approaches in dairy cattle

Evaluated aspect	Conventional mastitis detection	PLF-based mastitis detection
Monitoring type	Periodic, reactive	Continuous, proactive
Data collection	Manual observation, periodic milk sampling	Automated, real-time sensor data
Main indicators	Clinical signs, laboratory SCC	Online SCC, electrical conductivity, milk yield, milk composition
Detection of subclinical mastitis	Limited	High
Response time	Delayed	Early
Diagnostic accuracy	Moderate	High (especially with multi-sensor integration)
Decision support	Farmer experience-based	Data-driven, algorithm-supported
Antibiotic use	Often empirical	Targeted, reduced
Labor requirement	High	Reduced
Impact on animal welfare	Limited	Positive
Suitability for large herds	Low	High

As shown in Table 1, PLF-based systems provide clear advantages over conventional methods, particularly in terms of continuous monitoring, earlier detection, and data-driven decision support. However, improvements in diagnostic accuracy are strongly dependent on the integration of multiple indicators, as single-parameter approaches may produce inconsistent results (Rutten et al., 2013).

The literature consistently identifies SCC as the most reliable indicator of intramammary inflammation, reflecting the immune response of the mammary gland (Pan et al., 2025). However, single-parameter monitoring systems frequently show limited diagnostic accuracy. Milk electrical conductivity, although widely used in automated milking systems, is influenced by several non-pathological factors, resulting in variable performance for mastitis detection (Rukmana et al., 2021). As a result, recent studies emphasize multi-sensor approaches that integrate SCC, milk yield deviations, electrical conductivity and milk

composition parameters. Nevertheless, despite the generally positive results, variability in diagnostic performance has been reported across studies. While several studies report high accuracy of multi-sensor systems for mastitis detection, others highlight an increased rate of false positives, particularly when relying on single indicators such as electrical conductivity. This inconsistency suggests that detection performance is influenced by herd-specific conditions, environmental factors, and sensor calibration, emphasizing the need for context-specific validation of PLF systems (Banhazi et al., 2012; Rutten et al., 2013).

The application of machine learning techniques has significantly improved mastitis detection performance. By modeling complex, nonlinear relationships among multiple indicators, machine learning-based systems consistently outperform traditional threshold-based methods, achieving higher sensitivity and specificity, particularly for subclinical mastitis (Pan et al., 2025). In parallel, fuzzy inference systems have demonstrated satisfactory detection accuracy using a limited number of milk parameters, offering a cost-effective solution for on-farm decision support (Rukmana et al., 2021).

Overall, the literature converges on the conclusion that PLF-based mastitis monitoring enables earlier detection, reduces unnecessary antibiotic use, supports targeted treatment strategies and improves udder health management. From a practical perspective, these findings suggest that farmers can use PLF systems to optimize health monitoring strategies, reduce veterinary costs through early disease detection, and improve treatment decision-making, ultimately enhancing farm profitability (Steeneveld et al., 2015; Lovarelli et al., 2020). Despite remaining challenges related to sensor accuracy, data integration and economic feasibility, PLF technologies represent a key advancement toward proactive, welfare-oriented and sustainable mastitis control in modern dairy farming (Stanek et al., 2024).

Reproduction Monitoring in Cattle Using Precision Livestock Farming

Efficient reproductive management is essential for productivity and economic sustainability in cattle systems, yet conventional monitoring based on visual observation is increasingly unreliable due to reduced estrus expression and limited labor availability (Mottram, 2015). Precision Livestock Farming (PLF) technologies provide an effective alternative by enabling continuous, automated monitoring of behavioural and physiological indicators associated with reproductive events (Neethirajan, 2017). Activity-based monitoring using accelerometers is the most widely adopted PLF approach for estrus detection, as estrus is typically accompanied by increased locomotor activity and restlessness (Mottram, 2015; Tullo et al., 2019). These systems consistently outperform traditional observation, particularly in intensive dairy systems, although false positives may occur due to non-reproductive activity changes (Mottram, 2015). The integration of accelerometer data with other behavioural indicators, such as rumination and lying behaviour, combined with advanced data processing and machine learning techniques, has been shown to improve detection robustness and adaptability across management contexts (Tullo et al., 2019).

PLF technologies are also increasingly applied to calving prediction, a critical aspect of reproductive management. Behavioural changes, including increased tail movement and altered activity patterns, intensify during the hours preceding parturition and can be detected using automated sensors (Szenci, 2022; Sedó et al., 2024). Although prediction accuracy varies due to individual and environmental factors, these systems enable earlier intervention compared with conventional monitoring, contributing to reduced calving-related risks. An overview of the main PLF technologies used for reproductive monitoring, including estrus detection and calving prediction, is illustrated in Figure 1.



Figure 1. Precision Livestock Farming (PLF) technologies for reproductive monitoring in dairy cattle: estrus detection and calving prediction (created with https://biorender.com)

As shown in Figure 1, PLF systems integrate multiple behavioural and physiological indicators to support the identification of reproductive events. This multi-sensor approach enhances detection reliability compared with single-indicator systems, although performance remains dependent on data quality and farm-specific conditions (Norton & Berckmans, 2017; Lovarelli et al., 2020) Evidence from the reviewed studies suggests that PLF-based reproductive monitoring is associated with improved accuracy in detecting reproductive events while reducing reliance on manual observation. The findings indicate that combining multiple physiological and behavioral indicators through data-driven approaches enables earlier and more reliable identification of reproductive status compared to conventional monitoring methods (Rutten et al., 2013). Nevertheless, the effectiveness of these systems is not consistent across all studies. While some research reports high detection accuracy for estrus and calving prediction, other studies highlight moderate performance and the occurrence of false positives, particularly under variable environmental conditions or in herds with high behavioural variability. This suggests that predictive performance is influenced by both animal-related and management-related factors, requiring further validation under commercial farming conditions (Wathes et al., 2008; Banhazi et al., 2012). At the same time, the literature highlights that individual variability constrains the predictive performance of any single indicator used in isolation, supporting the added value of multi-sensor integration for more proactive and welfare-oriented reproductive management (Mottram, 2015; Tullo et al., 2019; Szenci, 2022). From a practical perspective, these findings suggest that farmers can use PLF systems to improve estrus detection accuracy, optimize breeding timing, and better anticipate calving events, thereby reducing reproductive losses, improving herd fertility, and enhancing overall farm efficiency (Steeneveld et al., 2015).

Body Weight, Body Condition Score, and Conformation Assessment

Body weight, body condition score (BCS), and body conformation are key indicators of animal health, nutritional status, productivity, and welfare, playing a central role in management and breeding decisions (Wathes et al., 2008; Berckmans, 2017). Conventional assessment methods based on manual weighing and visual scoring are often labor-intensive, subjective, and may induce stress, particularly when

applied repeatedly or at large scale. These limitations have driven the adoption of automated approaches within Precision Livestock Farming (PLF) systems.

Recent evidence shows that computer vision–based technologies enable accurate and repeatable estimation of body weight and morphological traits using 2D imaging, depth sensors, and 3D reconstruction techniques (Dohmen et al., 2022; Wang Y. et al., 2023). The extraction of body dimensions and shape-related features allows continuous phenotypic monitoring under commercial conditions, reducing animal handling and increasing the temporal resolution of growth and condition assessment compared with conventional methods. Automated body condition scoring has similarly benefited from PLF-based imaging systems. An overview of PLF-based approaches for body weight, body condition score, and conformation assessment is presented in Figure 2. This is particularly relevant in extensive or large-scale production systems where routine manual evaluation is impractical.

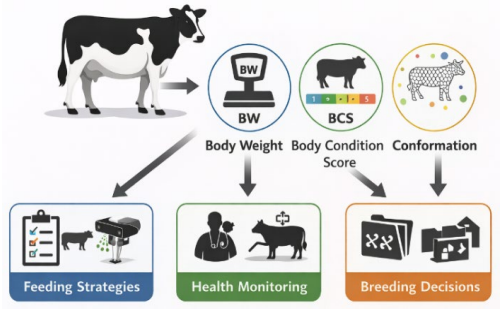


Figure 2. Precision phenotyping in cattle using body weight, body condition score and conformation traits to support feeding, health monitoring and breeding decisions (created with https://biorender.com)

As shown in Figure 2, geometric and surface features derived from dorsal or lateral views can be linked to BCS using machine learning and deep learning models, helping reduce observer-related variability and enabling earlier detection of suboptimal nutritional or metabolic conditions (Bewley et al., 2008; Halachmi et al., 2008; Song et al., 2019). However, the accuracy of these systems depends on image quality, animal positioning, and algorithm robustness, which may limit their performance under commercial farm conditions. At herd level, the integration of body weight and conformation data into PLF platforms supports dynamic monitoring of growth patterns, body reserve mobilization, and phenotypic variability across production stages (Martins et al., 2020; Wang Y. et al., 2023). At the same time, variability in system performance has been reported across studies. While some research demonstrates high accuracy and repeatability of computer vision–based methods, other studies highlight limitations related to model generalization and sensitivity to environmental conditions, suggesting that further validation is required before large-scale implementation (Norton & Berckmans, 2017; Dohmen et al., 2022). Overall, the synthesized results indicate a shift from sporadic, manual evaluation toward continuous and objective phenotyping, supporting more precise, welfare-oriented livestock management, despite ongoing challenges related to sensor calibration and model generalization (Norton & Berckmans, 2017). From a practical perspective, these technologies enable farmers to monitor animal condition more frequently and objectively, improve feeding management, and support timely interventions, thereby enhancing productivity and animal welfare.

Productivity Outcomes in Dairy and Beef Systems

The reviewed evidence indicates that the implementation of Precision Livestock Farming (PLF) technologies is associated with improved productive performance in both dairy and beef cattle systems, as illustrated in Figure 3, which highlights the main pathways through which continuous monitoring and data-driven decision-making contribute to enhanced productivity. Sensor-based, individual-level monitoring enabled more precise and timely management interventions, resulting in reduced performance variability and enhanced production consistency across herds (Lokhorst et al., 2019; Lovarelli et al., 2020).

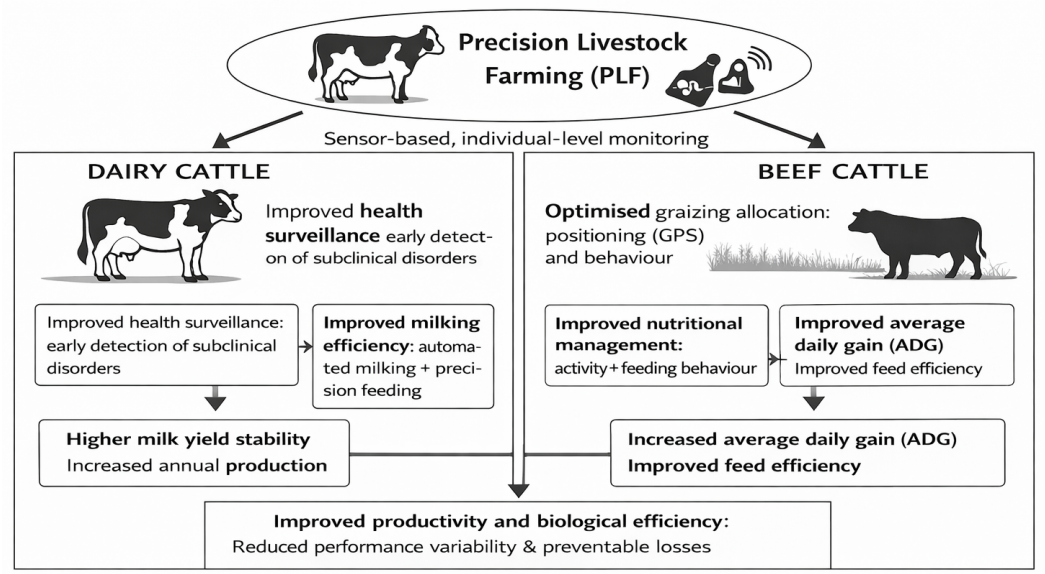


Figure 3. Precision Livestock Farming (PLF) pathways to improved productivity in dairy and beef cattle (created with https://biorender.com)

As shown in Figure 3, productivity improvements are primarily driven by the integration of continuous monitoring with timely, data-based management interventions at individual animal level. In dairy cattle, PLF adoption was primarily linked to increased milk yield stability and annual production per cow, largely through improved health management and milking efficiency. Continuous monitoring of rumination, activity, and milking behavior facilitated early detection of subclinical disorders, thereby limiting milk yield losses and improving lactation persistence. Automated milking and precision feeding systems further contributed to higher cumulative milk output under PLF-supported management strategies (Rutten et al., 2013; Steeneveld et al., 2015).

In beef production systems, PLF technologies were associated with improvements in growth performance, particularly through increased average daily gain and improved feed efficiency. Behavioral and positional monitoring supported optimized grazing and nutritional management, leading to more uniform growth and enhanced meat production. These effects suggest that PLF contributes to improved biological efficiency and resource utilization in beef cattle systems (González et al., 2015; Greenwood et al., 2017). At the same time, the magnitude of productivity gains varies across studies. While some research reports substantial improvements in milk yield and growth performance, other studies indicate more moderate benefits, particularly in systems where baseline management is already optimized. This variability suggests that the effectiveness of PLF technologies is influenced by farm-specific conditions, management practices, and the level of technology integration (Banhazi et al., 2012; Lovarelli et al., 2020).

Collectively, the findings support the interpretation that PLF enhances milk and beef production by improving biological efficiency and preventing avoidable performance losses. Productivity gains appear to result from the integration of continuous monitoring with targeted, animal-specific management responses, underscoring the role of PLF as an effective strategy for increasing cattle productivity while supporting animal welfare and production sustainability (Berckmans, 2014). From a practical perspective, these results indicate that farmers can use PLF systems to optimize feeding strategies, improve herd health management, and enhance reproductive efficiency, ultimately increasing

farm profitability and production sustainability (Steeneveld et al., 2015).

PLF in Extensive/Pasture-Based Systems

In extensive cattle production systems, Precision Livestock Farming (PLF) technologies improve management efficiency by enabling continuous monitoring of animal location, activity, and grazing behavior under conditions of limited direct supervision. GNSS-based tracking, accelerometers, and density-based data processing reduce information gaps inherent to pasture-based systems and support informed, animal-specific management decisions while preserving the low-input nature of extensive production, as depicted in Figure 4 (Aquilani et al., 2022).

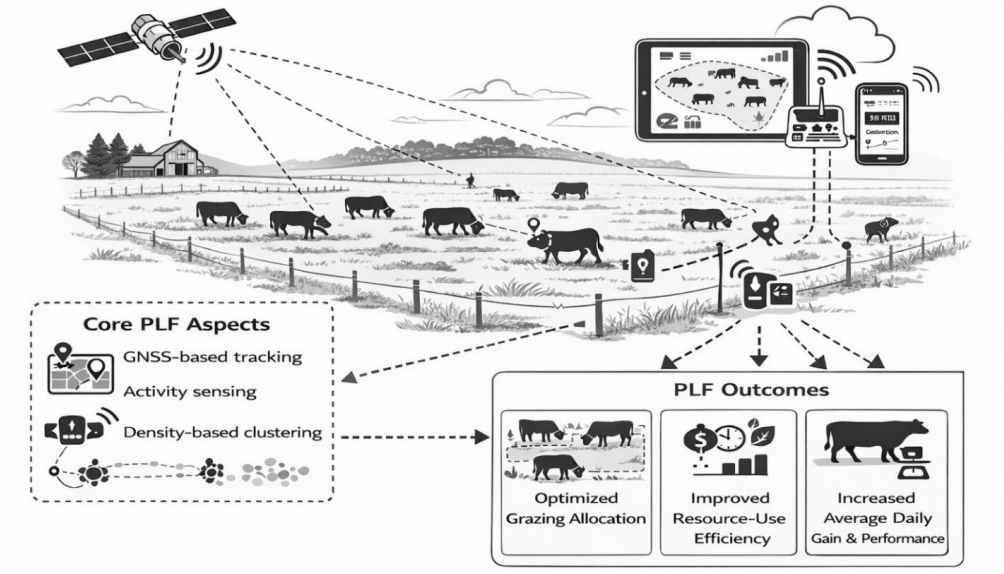


Figure 4. Precision Livestock Farming (PLF) in extensive and pasture-based cattle production systems: Global Navigation Satellite System (GNSS)-based monitoring, activity sensing and management outcomes (created with https://biorender.com)

As shown in Figure 4, PLF technologies enable the integration of spatial and behavioural data to support more precise grazing management and improved understanding of animal distribution and activity patterns in pasture-based systems (González et al., 2015; Williams et al., 2016). Evidence from grazing-based studies indicates that PLF applications allow objective quantification of pasture use and grazing time, which are closely associated with productive performance in extensive dairy and beef systems. The integration of GPS data with clustering algorithms enables accurate estimation of time spent grazing under variable pasture conditions, supporting improved assessment of feed intake opportunities and energy expenditure. This information facilitates more effective grazing management and stocking rate adjustments in highly dynamic forage environments (Williams et al., 2016). Even so, the adoption of PLF technologies in extensive systems remains constrained by several practical limitations. Data transmission challenges, sensor durability, and infrastructure requirements may reduce system reliability in remote or large grazing areas. In addition, economic considerations and the need for technical expertise may limit the willingness of farmers to adopt these technologies under extensive production conditions (Banhazi et al., 2012; Aquilani et al., 2022). From a production standpoint, PLF adoption in extensive systems has been linked to improved growth performance and resource-use efficiency, particularly in beef cattle. Optimized grazing allocation, early detection of behavioral or health deviations, and reduced handling-related stress contribute to increased average daily gain

and more uniform animal performance (Greenwood et al., 2017). At the same time, the magnitude of these benefits varies across studies, as environmental conditions, pasture availability, and herd management practices can influence system performance and limit the consistency of results. Although adoption remains limited, current evidence highlights the substantial potential of PLF to enhance productivity, animal welfare, and environmental sustainability in pasture-based cattle systems (Greenwood et al., 2017; Aquilani et al., 2022). These findings indicate that PLF technologies can support more efficient grazing management, better resource use, and enhanced decision-making in extensive cattle systems.

Environmental Implications: Emissions and Mitigation Potential

As illustrated in Figure 5, PLF technologies enable the continuous capture of animal-level data, including feed intake, feeding behaviour, rumination, and activity, all of which are closely associated with enteric methane production mechanisms (Wathes et al., 2008; Mottram, 2015; Berckmans, 2017).

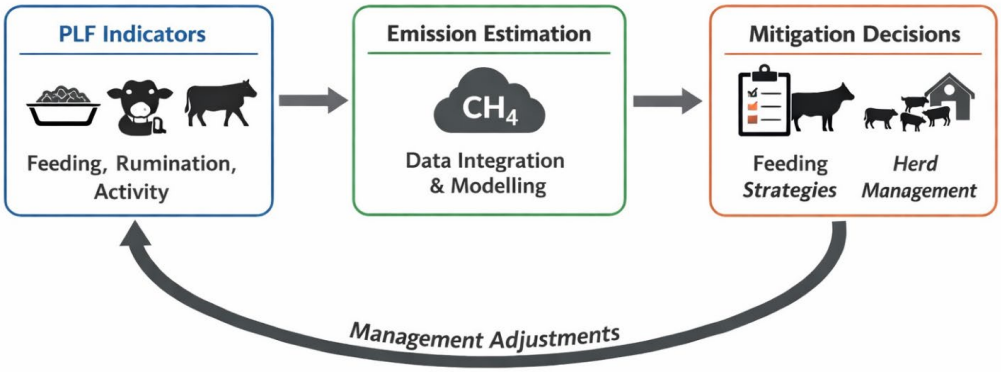


Figure 5. PLF-based framework for enteric methane (CH_4) emission estimation and mitigation through data-driven management decisions (created with https://biorender.com)

Figure 5 further highlights how the integration of behavioural, physiological, and production parameters supports more refined estimation of methane emissions and facilitates targeted mitigation strategies at both individual and herd level. In this context, PLF enables a more dynamic and animal-specific characterization of emission patterns compared with conventional assessment methods. Compared to conventional emission assessment methods, PLF enables a more dynamic and animal-specific characterization of emission patterns.

Evidence indicates that PLF-derived behavioural and physiological indicators can be used as indirect proxies for enteric methane emissions, supporting near real-time estimation under practical farming conditions (Tullo et al., 2019; O'Connor et al., 2024). Differences in feeding behaviour and feed efficiency between animals have been associated with substantial variation in methane emissions, reinforcing the value of PLF tools for identifying high-emitting individuals and supporting targeted mitigation strategies (Beauchemin et al., 2020). At herd scale, the integration of PLF data into dynamic modelling frameworks improves the representation of herd structure, productivity, and turnover, leading to more accurate estimates of total emissions over time (Rotz, 2018; Henn et al., 2023). These approaches allow emissions to be assessed in relation to production stages and management changes, thereby reducing uncertainty compared with static emission factor methods. Despite these advances, reliance on indirect indicators introduces important sources of uncertainty. Factors such as diet composition, environmental variability, and individual metabolic differences can influence methane production, potentially limiting the precision of proxy-based estimation under commercial farming conditions (Rotz, 2018).

Feeding management represents a key application area for PLF in emission mitigation. Precision feeding strategies, supported by continuous monitoring of intake and animal performance, enable the evaluation of dietary interventions aimed at reducing methane emissions while maintaining productivity (Beauchemin et al., 2020; Ouatahar et al., 2021). Available evidence indicates that mitigation efficiency varies considerably between systems, reflecting the influence of interacting biological and management factors such as diet formulation, animal variability, and production conditions.
Overall, the literature points toward a transition from retrospective emission assessment to more proactive, system-oriented emission management in livestock production systems (Wongpiyabovorn et al., 2025). These findings emphasize the role of PLF in supporting more informed management of feeding and production systems, facilitating a better balance between environmental impact and productive performance (Lovarelli et al., 2020; Ouatahar et al., 2021).

CONCLUSIONS

Precision Livestock Farming (PLF) provides a robust framework for improving cattle management by enabling continuous, objective monitoring and facilitating earlier, data-driven interventions at the individual animal level.
In both dairy and beef systems, PLF contributes to improved performance through integrated applications in welfare assessment, health surveillance (notably mastitis detection), reproductive monitoring, and automated phenotyping, thereby reducing preventable losses and improving production efficiency. The magnitude of these benefits varies across studies, as system performance is influenced by farm-specific conditions, data quality, and the level of technological integration. PLF also supports sustainability goals by improving resource-use efficiency, enabling better management of extensive pasture-based systems, and facilitating enteric methane emission estimation and mitigation, although wider adoption will require further validation and cost-effective implementation. At the same time, important challenges remain, including variability in sensor accuracy, limitations of proxy-based estimations, and economic and practical constraints affecting large-scale adoption. Overall, PLF represents a promising tool for enhancing productivity and sustainability in cattle systems, but its effective implementation requires context-specific validation, improved data integration, and greater accessibility for farmers.

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