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Smart technologies for sustainable pasture-based ruminant systems: A review

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ABSTRACT

Ruminant livestock farming is essential for providing high-value protein foods for humanity. Nevertheless, the environmental impact and sustainability of ruminant farming systems are under increasing scrutiny due to factors such as climate change and land degradation. Extensive pasture-based farming systems can mitigate these challenges, as they are associated with range of ecosystem services, although they are characterized by low efficiency and are labor-intensive and time-consuming. This review investigates the potential of Precision Livestock Farming technologies (PLF) to enhance the health, welfare, and productivity of grazing ruminants while minimizing environmental impacts. Precision Livestock Farming tools, such as GPS tracking, accelerometers, and virtual fencing, enable real-time monitoring of animal behavior, health, and pasture management, offering smart solutions to challenges such as overgrazing and greenhouse gas emissions. These technologies also enhance the integration of sustainable agronomic practices, like rotational grazing and nitrogen-fixing crops, which can improve soil health and reduce emissions. Despite these benefits, the adoption of PLF technologies in extensive pasture-based systems remains limited due to economic, technical, and infrastructural barriers. Further research is required to optimize PLF applications for various ruminant species, improve data accuracy, and scale these technologies for broader implementation in sustainable livestock farming. Additionally, future efforts should prioritize the integration of animal and pasture management practices to fully harness the potential of PLF in mitigating climate impacts and improving the efficiency of livestock systems.

1. Introduction

Intensive and extensive livestock production systems play a key role in satisfying the global demand for animal products. The trend in developed countries is toward increasingly intensive livestock production systems, resulting in reduction of the use of pasture-based systems [1]. However, pasturelands are one of the most important ecosystems in the world, located mainly on lands unsuitable for intensive agriculture [2,3]. Pasturelands provide multiple ecosystem services, including biodiversity conservation, soil erosion control, water and nutrient cycling regulation, and socio-economic benefits for rural communities [4]. In addition, pasturelands store approximately one-third of the global carbon stock, playing a crucial role in soil carbon sequestration [5]. These advantages result from the relationships between pasture management practices, pasture plants composition, soil conditions, animal behavior, and climate [6,7]. Promoting sustainable pasture

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management practices is essential to contribute to climate change mitigation [8]. Climate change will impact pasture-based ruminant farming systems, causing variations in the quality and quantity of grazing resources. This will lead to reduced animal performance and increased susceptibility to stress and diseases [9]. In this context, pasture-based systems must adopt practices to maximize efficiency and ensure responsible use of available resources, thus avoiding overgrazing or undergrazing, which are the main drivers of grassland degradation [10]. According to Horn and Isselstein [11], balancing environmental sustainability targets in animal production is essential for the future sustainable use of pasture-based systems. Smart technologies, such as Precision Livestock Farming (PLF), are potential tools to achieve this goal by optimizing resource management and investigating the relationship between animal and plant systems on pastures [12,13]. These technologies have been used for several years in housed livestock farms to improve management, but their application in pasture-based systems is still limited [14]. Although the use of these technologies in grazing systems is generating interest, further development and scaling up are needed to promote their application in ruminant's pasture-based systems [15,16].

This review, therefore, aims to provide an up-to-date overview of how digital technologies can enhance animal health and welfare, improve livestock performance, and contribute to the environmental sustainability of pasture-based production systems.

To conduct this review, a literature search was performed using the Google Scholar®, PubMed®, and Scopus® databases, focusing on relevant peer-reviewed articles published in English only (mainly between 2014 and 2024) to capture the most recent technological advancements of PLF in ruminant species. The key search terms used in various combinations were: "PLF technologies", species-specific terms ("cattle", "bovine", "sheep", "goat", "buffalo", "beef", "dairy") and relevant terms (e.g., "animal identification", "activity monitoring", "animal behaviors", "body weight", "virtual fencing", "pasture management", "grazing", "extensive", "health and welfare assessment", "environmental impact", "GHG emission").

2. Key issues on sustainability of grazing ruminants' production systems

Current grazing ruminant strategies are inadequate to simultaneously adapt grasslands to the increasing global protein demand and climate change due to their labor-intensive, time-consuming, and costly nature [10]. Additionally, these systems can significantly impact the environment, animal health and welfare, and farmers' economy [17]. In contrast, the adoption of improved grazing management techniques can potentially make these systems carbon negative. For instance, rotational grazing and the use of nitrogen-fixing forage legumes can reduce N_2O emissions [18]. Adaptive multi-paddock/rotational grazing systems enhance sustainability of livestock pasture-based systems by reducing greenhouse gas (GHG) emissions, overgrazing, manure mismanagement and soil erosion [18,19]. However, regular and frequent monitoring of animals can be difficult and demanding in extensive pastures [20]. Managing animals in extensive production systems is challenging, mainly due to absence of frequent human-animal interactions [21,22]. Furthermore, the seasonality of production and/or quality of pastures can fail to meet the nutritional needs of grazing animals sometimes leading to several problems, such as reduction of body weight and body condition score, and alterations of metabolic status up to starving condition [23,24]. Additionally, limited pasture resources can also result in frequent competition among animals [25]. Despite these limitations, grazing ruminant systems allow animals to express their natural behavior, maintain optimal health, and experience positive emotions [26].

3. Role of advanced technologies in livestock production systems

Recent technological advancements offer novel solutions to enhance animal management, productivity, and welfare [27,28]. The development of PLF results from interdisciplinary collaboration among animal scientists, physiologists, veterinarians, ethologists, engineers, information and communication technology (ICT) experts, and other related disciplines. According to Berckmans [29], PLF aims to manage individual animals through continuous, real-time monitoring of their health, welfare, production/reproduction, and environmental impact. Therefore, PLF technologies are designed to control key production related variables and alert farmers whenever any problems are detected [30]. A critical element of process control in PLF is the accurate prediction of how output variables (e.g., animal health metrics) respond to changes in input conditions, a method known as model-based control [29]. To identify animal discomfort, PLF tools focus on specific behavioral changes [16], and the development of alarm service, based on behavioral data, integrated into the process [31]. The data collected are used to create algorithms and models, serving as "golden rule" code for automatic identification and classification process [32]. In this context artificial intelligence will offer promising opportunities for advanced data processing and seamless integration of diverse sensor inputs, thereby enabling more effective livestock monitoring and management. Then, PLF systems can assess potential issues and provide alerts for decision-making support to farmers [33]. The frequency of data collection varies depending on the considered variable; for example, stress may require real-time monitoring, whereas weight can be assessed daily or weekly [29]. Many PLF devices are equipped with data processing systems that can promptly detect diseases, potentially preventing epidemic outbreaks among animals [34]. Furthermore, PLF application can ensure the safety and quality of the animal products and their traceability along the feed-animal-food chain [35,36]. The extensive data collected using various PLF tools requires the use of large storage devices or cloud services which currently represent a significant gap for a widespread adoption of PLF technologies [16,36]. Overall, according to Pomar et al. [37], the PLF system aims to: 1) identify optimal feeding strategies for livestock; 2) enhance resource management efficiency to minimize environmental impact; 3) coordinate crop management practices to ensure compatibility with livestock feeding needs; 4) guarantee food safety through product traceability processes; 5) improve animal health and welfare; 6) optimize crop productivity. Currently, PLF applications are driven by two major technological advancements: the use of big-data and advanced analytics capabilities, and the integration between aerial imaging, robotic feeding, milking systems, and smart sensors [38]. Originally designed for intensive farming, PLF technology is now being explored for implementation in pasture-based farming to address challenges related to livestock grazing systems [28].

4. Challenges of applying advanced technologies in sustainable grazing livestock farming

The application of PLF technologies in extensive farming faces several challenges [38]. Extensive farms often cover large areas of land with significant topographical variations, making difficult to use monitoring technologies such as sensors and cameras, which require uniform coverage and accessible terrain and stable internet connectivity for data transmission [36,39,40]. Furthermore, access to electricity may be limited in remote rural areas complicating the installation of electrically powered devices unless reliable alternative, such as solar power and/or supplementary battery, are available [41].

According to Tedeschi et al. [38], the application of PLF tools for livestock extensive pasture-based systems requires measurement technologies that can be either "on-animal" or strategically placed in locations frequently visited by animals, such as watering and supplementary feeding points. These technologies can provide large-scale measurement of animal, pasture, and landscape using aerial or satellite imagery with wireless data processing and transmission suitable for extensive livestock systems.

To improve the sustainability of animal grazing systems, both pastures and livestock should be considered and managed as an integrated system [12,42]. Moreover, due to the variety of ruminant species that can be reared in grazing conditions, it is fundamental to adapt PLF technologies by considering specie-specific biological and behavioral differences and validating them with evidence-based scientific data.

4.1. Assessing and managing pastures using Precision Livestock Farming technologies

Pasture productivity depends, in addition to climatic and pedological conditions, on the optimal use of grazable areas [43]. Regular assessment of pasture biomass and growth rates is crucial to avoid over- and under-grazing, with direct measurements, such us destructive sampling or the use of plate meters, are considered the most accurate but labor-intensive and time-consuming [44,45,46]. Currently, efforts to automate these measurements are promising, but challenges related to data accuracy and availability limit their widespread adoption [47]. Emerging technologies, such as remote pasture measurement devices and drones with Geographic Information System (GIS) analysis, offer efficient pasture assessments [48,49]. However, critical issues, such as meteorological conditions (e.g., cloud cover), and insufficient spatial and temporal resolution, can limit timely pasture management [28,50]. Calibration of these technologies is essential for accurate biomass measurements, though it can introduce significant errors [46,51]. Indirect calibration, using ground measurements instruments like the rising plate meter or the pasture reader, are viable alternative [52]. Integration of satellite technology with electronic rising plate meter has proven effective in reducing manual labor providing finer-scale biomass measurements within paddocks [53].

Additional factors in optimizing pasture management include the requirement to fence off different grazing areas and continuously monitor grazing livestock [12,42]. The virtual fencing (VF) technology allows livestock management and monitoring without physical boundaries, improving pasture productivity and biodiversity conservation [54]. This technology utilizes Global Positioning Systems (GPS) integrated with conditioned pre-warning signals and deterrents (e.g., auditory, vibratory cues, or electronic shocks) to direct grazing animals towards more productive areas while preventing access to overgrazed or ecologically vulnerable areas [55]. To date, four global companies (Agersens eShepherd, Australia; Nofence, Norway; Vence, California; Halter, New Zealand) are developing and marketing virtual control systems, but market penetration remains low. They are developing collars and position transmission data via GPS to empower farmers to remotely set pasture boundaries using applications on smartphones, tablets, or PCs [11]. However, VF systems are not yet widely used worldwide due to differences in the legal constrains of single nation. Therefore, further demonstration and clear guidelines for its appropriate use need to be established. The absence of negative impacts on animal behavior and welfare, suggest promising prospectives in managing pasture areas with VF [56]. Integrating remote sensing data from Unmanned Aerial Vehicles (UAVs) with animal behavior data collected from VF collars offers significant potential for enhancing pasture management. This approach enables the link of animal behavior with grass cover, thus providing valuable insights into biomass availability [42]. VF technology has also the potential to reduce the labor demands, allowing farmers more time to other routine tasks and thus achieving a better work-life balance [57]. Additionally, VF could support grazing activities in previously abandoned areas, protected habitats, riparian zones, moorlands, locations susceptible to soil erosion, and hazardous areas to animals [11].

4.2. Monitoring and managing grazing animals using Precision Livestock Farming technologies

Besides managing pastures, PLF technologies contribute to the sustainability of extensive farming systems by using advanced technologies to monitor and manage animal behavior, health, and welfare during grazing periods. In this context, many efforts are ongoing to collect more data remotely from grazing animals [28].

4.2.1. Individual identification and location

Monitoring individual animals requires a PLF approach based on the collection of data related to individual characteristics [58]. Visible ear-tagging and Radio Frequency Identification (RFID) systems are widely used for animal identification. Ear-tags involve a plastic label with a unique number, while RFID utilizes radio waves to wirelessly transmit an electronic code containing animal data [59]. Despite its advantages, RFID adoption is limited due to concerns about data security, including the potential for tag-content alterations and system spoofing [58]. A more complex method involves computer vision and data analysis offering a rapid and secure solution for species or animals' identification. This system is designed to recognize unique animal phenotypes, such as muzzle, retinal vascularity, and coat patterns [60]. Currently, Machine Learning and Deep Learning techniques are increasingly being used to extract these phenotypes for individual animal identification [61]. However, these techniques require the installation of devices at key crossing points or fenced resting areas for animals.

Individual monitoring is used to track animal locations during grazing periods. By attaching GPS collars or ear-tags to animals, farmers can receive real-time data on animal locations [28,62]. Additionally, livestock tracking and geofencing can be supported by Internet of Things (IoT) technology which helps farmers to quickly locate any lost animals, ensuring their health and well-being [63].

4.2.2. Environmental conditions

Assessing environmental conditions is highly valuable in extensive farming systems, where animals are more exposed to external climatic conditions compared to indoor farming. In extensive systems, monitoring animal thermal comfort can guide grassland arrangements, such as planting density and row orientation, to enhance thermal comfort and mitigate extreme conditions. For example, silvopastoral systems have been shown to improve animal adaptation to climate change by reducing heat stress [64].

Real-time monitoring of thermal stress using environmental and on-animal sensors allows for early alerts [65]. Various technologies, including ear canal sensors, rumen boluses, accelerometers, rectal and vaginal probes, GPS or Global Navigation Satellite Systems (GNSS) and thermography, are commonly used to monitor body temperature and behavioral responses to heat stress [66,67]. Among these, accelerometers are particularly useful for detecting changes in activity related to heat stress in grazing animals, which are vulnerable to high temperatures and direct solar radiation [67]. Additionally, real-time tracking can also determine water availability in extensive pastures. Bailey et al. [20,68] demonstrated that on-animal sensors and GPS tracking can detect failures in water systems by observing abnormal animal behavior, such as prolonged stays near water sources. Infrared thermography (IRT) or thermal imaging represents a sensor-based and non-invasive technology for measuring body surface temperatures, either through environment sensors or handheld devices [69]. Thermography was used for measuring body surface temperatures in beef cattle [70] and buffaloes [71], while digital surface temperature monitors were used to measure ear surface temperature in dual-purpose cattle under grazing conditions [72]. These studies showed the advantages of measuring body temperature to provide a more comfortable microclimate in grazing systems, such as integrating crop-livestock-forestry systems which enhances thermal comfort and promoting the rational use of natural resources [70]. Weather stations can also record various climatic variables (e.g. precipitation, air temperature, relative humidity, wind speed and direction) in grazing systems [73,74,75,76,77,78]. These studies highlighted how weather conditions can significantly affect animal behaviors and the animals' daily walked distance on rangelands.

4.2.3. Animal behavior, health and welfare

Pasture-based systems offer significant welfare benefits by allowing animals to express natural behaviors [79]. According to Vázquez-Diosdado et al. [80], PLF systems improve animal welfare surveillance allowing earlier detection of issues thus enhancing decision-making and timely interventions. Herlin et al. [79] reported that sensors, measuring animal behavior and physiological parameters on pasture, can monitor welfare status, with alarms triggered as consequence of deviations due to condition of disease, pain, and heat stress. Commonly monitored behaviors in animals include grazing, resting, eating, drinking, walking, running, ruminating, lying, and standing. Wearable 3-Dimensional (3-D) accelerometers have shown promise in accurately identifying these behaviors when combined with robust analytical methods [68,81,82]. Machine Learning further improves the accuracy of behavior recognition, thus facilitating animal health and disease tracking [83]. In addition to wearable 3-D accelerometer, nose-band pressure and sound sensors can be also used to monitor feeding behavior in grazing animals [84,85]. Högberg et al. [86] highlighted the effectiveness of rumination detection sensors for assessing sudden changes in rumination activity, potentially indicative of health issues, such as subclinical nematode parasitism in grazing sheep [87]. However, further development is needed to fully integrate PLF technologies for managing parasitic infections in grazing livestock [88,89]. Accelerometers can assist farmers in detecting other health concerns including parturition events [90,91], post-calving difficulties [92], and bovine diseases such as the bovine ephemeral fever [93]. Wearable 3-D accelerometer sensors can be integrated into ear tags [90], collars [93], or pH boluses [94], attached to hind legs [92] with GPS tracking to support in disease detection and behavior classification [95]. Unmanned Aerial Vehicles (UAV) equipped with cameras, Light Detection and Ranging (LiDAR), infrared sensors, GPS, acoustic sensors, and gas sensors have the potential to revolutionize livestock management in grazing systems by monitoring health, welfare, and nutritional deficiencies [79,96]. Ren et al. [97] combined a multicamera video recording system with an ultrawideband real-time location system (UWB RTLS) to detect standing and lying behaviors of sheep.

4.2.4. Animal feed and methane production control

Animal feed intake efficiency has a crucial role within rangeland ecosystems, enhancing pasture productivity and optimizing livestock production. Wireless sensor networks, combined with big data methodologies, represent useful tools for assessing pasture intake, a key factor for livestock efficiency [98]. Various methods are available to estimate herbage dry matter intake (DMI) of grazing cows, although they are labor-intensive, costly, not practical for daily use, or fail to provide individual average intake [99]. The DMI of grazing animals can be estimated based on the total number of eating chews and the corresponding bite mass. Andriamandroso et al. [100] classified the devices for the individual jaw movements into: jaw switches, pressure sensors, microphones, accelerometers, and electromyography. These devices detect jaw movements through different mechanisms such as sound patterns or muscle activity. However, bite mass estimation is complicated by the interaction with sward characteristics like height and density [101]. Rising plate meters are useful for assessing herbage mass before and after animal grazing. Alvarez-Hess [102] measured grazing behavior using jaw movement sensors, and DMI by herbage disappearance measured daily and hourly with a rising plate meter.

Ruminants, especially cattle, are the most criticized farming animals for having a high environmental impact as they are considered a direct source in the production of GHG, mainly methane, carbon dioxide and nitrous oxide [103]. Ruminant's methane emissions are positively correlated with forage intake, feed efficiency and associated with digestive fermentation processes [104]. To mitigate GHG emissions, strategies like rotational grazing, increasing legume consumption and utilizing plant species with secondary metabolites (e.g., tannins, saponins), have been proposed to modulate rumen microbiota and improve forage digestibility [105]. Respiration and accumulation chambers are considered the gold standard for directly quantifying methane emissions from ruminants [106]. However, their use with grazing animals poses significant challenges. For estimating emissions from free-ranging ruminants, various field measurement techniques have been developed [107]. Modified head-mask methods based on "spot sampling" protocols have been proposed, although resulting in datasets with high variability and only short-term emission rates [108,109]. Portable accumulation chamber (PAC) is also a device often used for grazing sheep, but it can detect relative changes in emissions rather than measuring total daily methane production [110,111,112]. Methane "sniffers", placed near feed bins, offer an alternative approach (Fig. 1A). They measure the CH_4 concentration in the animal's breath during feeding, while the simultaneous measurement of CO_2 concentration enables more accurate assessments [108,109,113]. However, the results are highly variable due to factors such as muzzle movement, feed intake, and air mixing [109]. Indirect tracer methods, such as in situ gas measurement tracers and gas sensors capsules, have also been developed for GHGs detection. Gas sensors capsules detect and monitor rumen concentrations of CH_4, H_2 and CO_2 but fail in measuring their flux emission [106] (Fig. 1B). The continuous release of sulfur hexafluoride (SF_6) has become the preferred method, by the insertion of a permeation tube into the rumen to measure the CH_4:SF_6 ratio in the animal's breath [114] (Fig. 1C). Although this method presents practical challenges, standardized procedures have been established to address them [115].

Other techniques include laser methane devices, open-path Fourier transform infrared (FTIR) spectroscopy, open-path laser technologies, mass balance, flux gradients linked to micrometeorological models (e.g., eddy covariance), and inverse dispersion methods. These techniques analyze atmospheric methane alongside weather data to estimate emissions at the herd or farm level [116,117,118,119]. Infrared CH_4 and CO_2 sensors, as well as the GreenFeed system, have been used to monitor methane production from individual animals [120,121]. Despite these advancements, accurately measuring and predicting methane production from individual grazing animals remains a significant challenge [106].

4.2.5. Animal productive and reproductive performance

Several key aspects must be considered in evaluating productive performance of animals raised for meat, including feed conversion ratios, weight gain over time, and meat quality [122]. Walk-over-Weighing (WoW) systems allow detailed measurement of individual responses to nutritional management [123]. Electronic identification, automated weighing systems, and wireless data transmission allow collection of frequently liveweight data, across livestock classes and environmental conditions [124]. The WoW systems are generally installed at entry points to feeding or watering areas, where animals can be automatically identified and weighed [125].

Tools such as 2- and 3-D sensors are used to estimate Body Condition Score (BCS) and body shape. According to Qiao et al. [58], 3-D sensors provide more detailed body surface information compared to 2-D or thermal image systems. Common 3-D sensors include Time of Flight (ToF) cameras and Microsoft Kinect cameras. Recently, Yurochka et al. [126] utilized a mobile BCS evaluation system for grazing animals. Los et al. [127] presented methods for estimating body dimensions (e.g. height and weight) of individual cows by stereo RGB imagery, video, and LiDAR data from UAVs. Their findings suggested the potential of UAVs body size measurement in extensive beef production systems, although accurately capturing individual cows from all angles remains challenging.

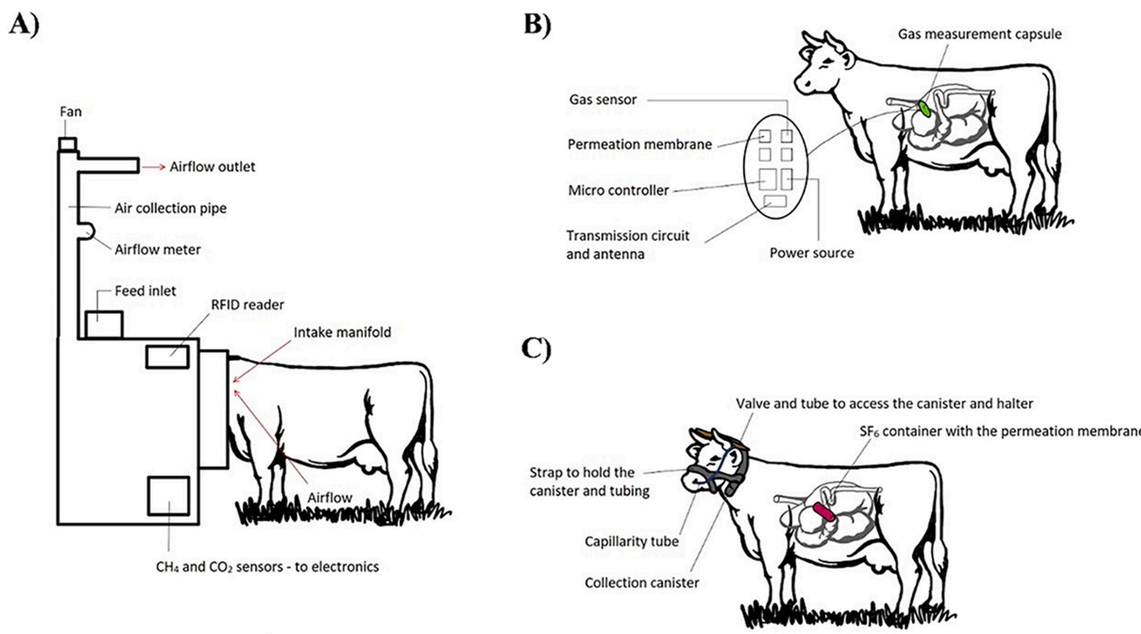

Fig. 1. Representation of different gas measurement methods in grazing ruminant species A) GreenFeed system, B) Gas Sensor Capsules, and C) Tracer Gas Sensor capsules.

Observing and identifying estrus in grazing animals is difficult due to animals' dispersion across large areas. The PLF technologies for estrus detection can reduce labor costs while enhancing the accuracy of heat detection [128]. An alternative strategy is the use of wireless intravaginal probes [129]. Additionally, monitoring behavioral patterns such as feeding, drinking, or lying can help in detecting reproductive events like calving [130]. GPS systems can also transmit coordinates of calving animals [131] or monitor the location of bulls, ensuring they remain within designated pastures. Real-time alerts generated when bulls stray from their assigned herds, may facilitate the monitoring of natural mating schemes [68].

4.2.6. Predation

PLF offers farmers a range of tools and techniques to mitigate the risk of predation on grazing livestock, especially during vulnerable periods, such as at night or in open pastures [28,132]. These tools include cameras, sensors, and GPS trackers [133,134,135], allowing farmers to track animal movements, activity levels, and alterations of heart rate and body temperature, identifying increased predation risks and thus implementing preventive measures [79]. Another approach, known as the "virtual shepherd" method, involves strategically moving animals to areas with low predation risk [136]. Riego del Castillo et al. [135] developed a robotic "SheepDog" capable of discriminating potential predators and/or harmless species for sheep flocks. Global Navigation Satellite System, Low-Rate Wireless Personal Area Networks (LR-WPAN), and Inertial Measurement Unit (IMU) systems are PLF technologies able to transmit real-time alerts to farmers when predation or worrying behavior is detected [137]. An example is the "e-Pasto" virtual fencing system, which uses collars equipped with motion sensors to track animals' location and behavior, by transmitting data wirelessly, using SIGFOX©, to a central server and then to the farmer [138].

4.2.7. Genetic management

PLF technology can significantly play a pivotal role in the genetic management of grazing-based livestock systems by offering precise and data-driven insights into individual animal performance and genetic potential. Through advancements in sensors, data analytics, and genomic tools, PLF enables farmers to accurately monitor valuable genetic traits, such as growth rate, milk production, disease resistance, and reproductive efficiency [38]. This information empowers farmers to make informed decisions regarding breeding selection, thereby improving the overall genetic merit of their herds for future generations. Additionally, PLF technologies facilitate the identification of superior animals for breeding, promoting genetic diversity and resilience in livestock populations adapted to various grazing environments [139]. Furthermore, PLF support enables high-throughput phenotyping, which can significantly improve the genetic selection for traits related to animal resilience [140]. By integrating genetic data with real-time monitoring of animal behavior and health, PLF enhances the efficiency and sustainability of genetic improvement strategies in grazing systems, ultimately contributing to increased productivity and profitability, maintaining animal welfare and environmental stewardship [141].

5. Current applications for animal grazing management in the pasture-based system

Smart technologies are revolutionizing the way farmers monitor, manage, and optimize health, productivity, and environmental impact. Specific applications across different ruminant species are illustrated in the following sections enhancing sustainability, efficiency, and animal welfare through PLF. Based on the literature reviewed in this study, Fig. 2 presents a heatmap illustrating the geographical distribution of research on PLF technologies in grazing ruminants. Visualization highlights the regions where these technologies have been more extensively studied, offering valuable insights into global research trends.

Additionally, Table 1 outlines the strengths and weaknesses of PLF technologies specifically tailored for ruminant grazing systems.

5.1. PLF technologies for dairy cattle

Precision Livestock Farming (PLF) technologies for grazing dairy cattle are becoming increasingly widespread, but their large-scale implementation is still in a growing phase, and highly dependent on available resources and local infrastructure. In a 2023 review, Heins et al. [168] examined all precision technologies available to dairy grazing farmers, highlighting a wide range of different technologies, with different functions, developed and marketed for dairy cattle, including wearable sensors, autonomous vehicles, and virtual fencing. A

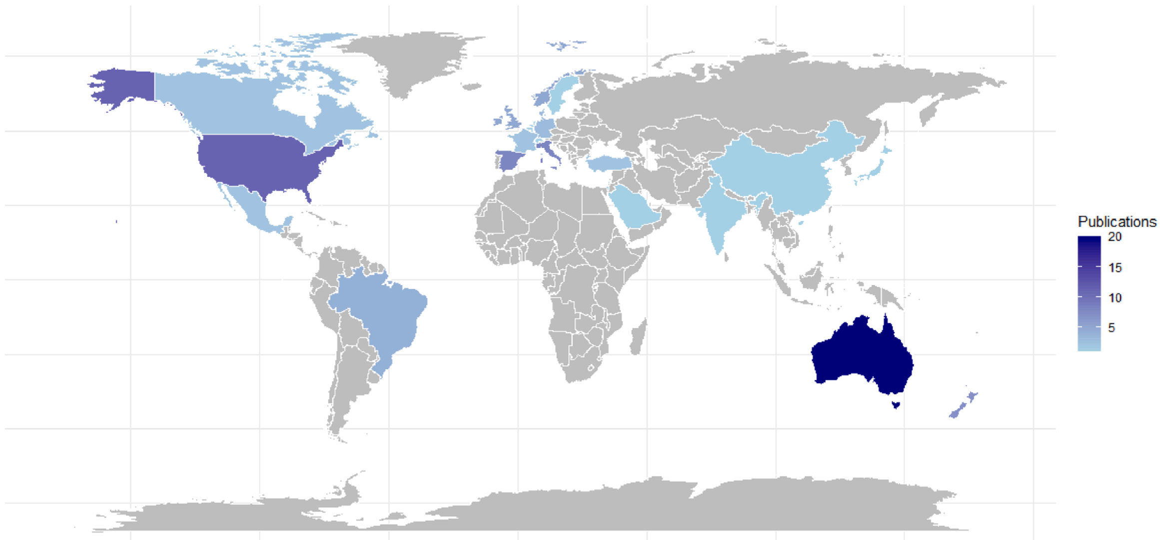

Fig. 2. Heatmap of the geographical distribution of research on PLF technologies in grazing ruminants based on the reviewed literature.

survey conducted by Bianchi et al. [169] highlighted reproductive management systems, supported by reliable activity sensors, as the most useful and widely adopted.

Talukder [170] suggested the use of infrared thermography for the estrus and ovulation detection, even if with some limitations related to accuracy and false positives. The author also proposed the use of accelerometers to monitor activity and rumination as potential indicators of estrus, albeit with the need to improve specificity. Brassel et al. [128] evaluated a novel accelerometer-based estrus detection collar for seasonal-calving dairy cattle on pasture utilizing a multimetric behavior recognition approach. Their results showed that this automated estrus detection system had high sensitivity. According to the authors, multimetric analysis of behavioral data is the most effective approach for improving estrus monitoring for dairy cows on pasture. In addition to collars, accelerometers for heat detection on grazing dairy cows can also be integrated into pedometers and ear tags (e.g. SCR Heatime Pro+ and AfiAct II Pedometer, IDS i-QUBE, [171,172,173]). On dairy grazing systems, it is also important to monitor reproductive events such as calving. Calcante et al. [131] suggested that GPS systems sending location coordinates of the animals during parturition may be used for calving detection in extensive dairy rearing systems.

Measuring grazing and rumination behavior may be a valuable approach for monitoring health and welfare of grazing dairy cows, as these are the predominant activities in dairy cows on pasture [174]. They reported that dairy cows on pasture spend most of the daytime grazing and most of the nighttime ruminating. The accuracy of the AfiCollar, a sensor-based device designed for real-time monitoring of these behaviors, was evaluated and found to be reliable, although minor adjustments to the algorithm could further improve its precision [175]. Similarly, ear tag accelerometers, such as Smartbow and CowManager, are used to monitor rumination and activity, providing health alerts for early detection of health issues [171,176]. Some ear tags, such as CowManager, can also measure ear temperature, which is useful for evaluating health conditions.

Noseband sensors can also be used to measure grazing and rumination behaviors in dairy cows. Werner et al. [177] showed that the noseband RumiWatchSystem sensor is an accurate research tool for measuring these behaviors. The authors reported a strong correlation between visual observation and RumiWatchSystem data for time budget, grazing bites and rumination chews. The RumiWatchSystem has gained widespread use, particularly in research involving grazing dairy cows. In pasture settings, accelerometer-based sensors can be enhanced with GNSS technologies, providing additional data for classifying dairy cow behaviors [178]. At an experimental level, the development and use of open-source tracking devices for behavioral monitoring are also becoming increasingly common in grazing dairy systems [179]. These devices integrate accelerometer, gyroscope and GNSS sensors [179]. Additionally, reticulum and ruminal boluses, such as SmaXtec, are widely used in grazing dairy systems to monitor animal activity, rumen temperature and pH, making them valuable tools for monitoring the health and welfare of dairy cattle [180].

In the dairy sector, milk yield and composition, such as milk volume, fat content, protein content, and somatic cell count, are also fundamental parameters for assessing production performance even in pasture-based systems [181]. Automatic milking systems (AMS) are mainly widespread in indoor dairy systems but are also becoming common in extensive pasture-based systems, like in Northern Europe and Australia [182]. Properly equipped milking robots can provide data on milk yield, milk flows, and milk composition, as well as monitor indicators of mammary health, such as milk electrical conductivity, color, and somatic cell count [183].

Finally, virtual fencing systems (e.g. Nofence or eShepherd) are being used in the grazing dairy sector [184,185], particularly in regions with large pasture areas. These systems are more commonly implemented in countries like Australia, USA or New Zealand whereas they are not yet commercially available in some EU countries.

5.2. PLF technologies for beef cattle

Precision Livestock Farming technologies are increasingly applied to beef cattle in grazing systems to improve overall management efficiency and animal welfare. Among these technologies, GPS tracking systems provide a pivotal role in monitoring cattle movements across extensive grazing lands, providing insights into grazing behavior and herd dynamics. Pretto et al. [162] introduced an innovative low-cost method for identifying beef cattle and recognizing their basic activities, specifically using ear-tags and tracking water ingestion with an Optical Character Recognition (OCR) algorithm. Similarly, Maroto-Molina et al. [186] introduced an IoT-based system that employed GPS collars and Bluetooth tags, integrated with the Sigfox network, to collect cattle location data. Ilyas and Ahmad [63] proposed an IoT solution for tracking grazing animals including geofencing applications. Whereas Nyamuryekung'e et al. [150] compared the daily distance walked estimation, obtained by GPS data alone or combined with 3-D accelerometers, for a better investigation of animal welfare implication in grazing conditions. In Australian grazing cattle, Corbet et al. [187] used ear-tags combined

Table 1
Strengths and weaknesses of Precision Livestock Farming technologies/tools applied in grazing ruminant systems.

Technology/sensor/tool	Applications	Strong sides	Weak sides	Species	References
Electronic identification (EID)	Individual identification, disease, stress assessment	Accurate tracking, health monitoring, improved record keeping, labor efficiency	Cost, data security, loss of tag, tearing of ear, breakage, failure	Cattle, Sheep, Goats	[40,58,142]
Injectable or implantable sensors	Stress assessment	Reduction of losses and tissue damage	Not widely used, bolus's specific gravity required	Sheep	[143]
	Disease detection	Continuous subcutaneous temperature monitoring	Migration and difficulty of removal	Sheep	[144]
Accelerometers	Animal behavior, welfare and health monitoring	Robust and mature technology	Interpretation and validation of data are continuously evolving	Sheep, Goats	[87,145]
	Body temperature, heart rate and heat stress assessment	Early detection of diseases, stress or death	Implantation method requires development for grazing application, real-time communication technology needs to be integrated	Cattle, Sheep	[65,66,67,146]
Rumen boluses	Individual identification, body temperature, rumen pH, activity	Accurate identification, health and activity monitoring, no losses	Low battery lifespan, no removable, problems with recovery at the slaughterhouse, potential retention issues for sheep and goats	Cattle, Sheep, Goats	[94,142,143]
GPS sensors	Animal position	Real time data on animal movement and spatial distribution	Low battery lifespan, lack of wireless data transmission	Sheep	[147,148]
	Behavior and welfare monitoring	Identification and characterization of sites preferred by animals, well-being alteration detection	Methods and data analysis need to be integrated	Cattle	[149,150]
	Calving monitoring	Calving prediction	Low battery lifespan, high cost	Cattle	[130]
	Predator detection	Quantify and predict spatial risks of predators-cattle encounters and related depredation.	Methods need to be integrated	Cattle	[132]
Acoustic, pressors sensors	Feed intake assessment	Discrimination between grazing and ruminating activities; low computational cost	Tested on limited number of animals	Sheep	[151]
			Needs to improve recognition performance	Cattle	[152,153]
Virtual fencing collars	Surveillance of pasture area and livestock	Animals moved in response to changes in forage availability	High cost, high learning variability between animals, lack of technological infrastructure in sheep farms	Sheep	[154,155]
	Behavior and welfare monitoring	Animal behaviors assessment	High cost, high learning variability between animals	Cattle	[156,157]
	Fuel breaks	Wildfires prevention	High cost, high learning variability between animals, lack of data on the topic	Cattle	[158]
Unmanned aerial vehicles	Surveillance of pasture area and livestock	Remote control of grazing animal	Improve accuracy, local regulations do not allow drones flying in restricted area	Cattle	[159]
	Animal performance	Accurate recognition of animal morphological traits	Animals are frightened by drones flying above, local regulations do not allow drones flying in restricted area	Cattle, Sheep	[16,127]
Cameras	Predator detection	High accuracy	High cost	Sheep, Goat	[134,135]
	Behavior and welfare monitoring	Cost-effective and reliable solution	Needs to be integrate with GPS data, reliability of the method	Cattle, Buffalo, Cattle	[160,161,162]
Electronic weighing platforms	Weight and growth monitoring	Frequent weight monitoring, alert for weight gain anomalies	Voluntary access through the scales	Cattle, Sheep	[125,163]
	Measurement of routine daily live weight	Data recorded without human intervention, high levels of accuracy of WoW platform	Animal adaptation to routinary use of WoW technology	Sheep	[164]
Infrared thermography	Thermal status	Reliable, precise, cost-effective and non-invasive technique	Climatic conditions can affect the interpretation of infrared imaging data	Sheep	[165]
	Detection of ovulation	Cost-effective and non-invasive technique	Methods and data analysis need to be integrated	Cattle, Buffalo	[71,166]
Gas sensors	Methane production detection	Minimal interference from other gases	Not applicable for grazing system; accurate detection protocols are required.	Cattle, Sheep, Goat	[112,118,119]
Methane sensors (sniffers)	Methane emission intensity	Evaluation of methane emission in grazing system, accurate phenotyping	Voluntary access through the sniffer	Cattle	[120,121]
Automated Robotic Dairy	Improvement of profitability and productivity of pasture-based dairy farms	Reduction of labor requirements, increase the competitiveness of pasture-based dairy system	High investments	Cattle	[167]
Rising plate meters	Grass height and mass assessment	Optimization of grass utilization	Labor-intensive and time-consuming	Ruminants	[45,46]
Satellite Remote sensing	Grass mass assessment	Reduction of the time required to manually monitor pasture biomass	Low accuracy of uncalibrated satellites	Ruminants	[50,53]

with a Walk-over-Weighing system near a cattle access water point to predict postpartum estrus events. Arshad et al. [146] implemented a wireless sensor network and artificial neural networks to predict cattle diseases.

Automatic monitoring also tracks feeding behavior to monitor animal health, growth conditions, and disease warnings [83]. PLF facilitates precise feed management through real-time data on nutritional needs and forage quality, optimizing feed efficiency and ensuring adequate nutrition for cattle [188]. Knight et al. [189] conducted a study on intake and grazing activities using RFID technology, GPS collars and GrowSafe® technology to monitor the dry matter intake of alfalfa hay. Andriamandroso et al. [190] developed an open-source algorithm to detect cattle grass intake and ruminating behaviors using an Inertial Measurement Unit from a smartphone. Asher and Brosh

[188] developed a Decision Support System by monitoring cows' daily activities, energy balance, and forage quality. Estell et al. [191] compared foraging behavior of mature Raramuri Criollo and Angus Hereford crossbred cows grazing in desert rangelands, observing their licking behaviors. Similarly, Simanungkalit et al. [192] monitored licking behavior using an ear-tag accelerometer and radio-frequency identification system. McCarthy et al. [193] used an electronic feeder to measure mineral and energy supplement intake in extensive pasture scenarios. Williams et al. [75] proposed a method for monitoring animals' water behavior by utilizing RFID technology to track water point usage in relation to climate and water availability. Menzies et al. [194] used the same technology to assess maternal parentage by the temporal frequency that cows and calves visit water points in extensive beef herds. Singh et al. [160] proposed a Machine Learning approach combined with video capturing to monitor grazing cattle behaviors in large herds. Hamidi et al. [195] emphasized the importance of understanding the relationship between grazing intensity and animal behavior for the development of smart technologies. Spedener et al. [196] identified factors influencing the habitat selection for both grazing and resting cattle using GPS collars and activity sensors. Hassan-Vásquez et al. [149] evaluated the potential of GPS collars data, to characterize the distribution of cattle dung in paddocks, paying special attention to the identification of hotspots with an excessive nutrient load. Arablouei et al. [197] used accelerometry data to classify cattle behaviors, whereas Wang et al. [198] for the same classification used neural networks models. Debauche et al. [199] and Park and Park [200] proposed a cloud-based monitoring system for investigating grazing cow behaviors.

The development of fenceless livestock control, known as virtual fencing systems, shows a positive impact on both livestock grazing management and conservation of natural habitats. Virtual fencing systems by using adverse stimuli to influence cattle movement and behavior in the absence of physical barriers do not influence animal welfare [55,201,202]. Confessore et al. [203] and Sonne et al. [204] confirmed no significantly modified stress indicators, such as manure cortisol levels, in cattle controlled with virtual fencing technology.

Versluijs et al. [156] used random forest models to classify free-ranging behaviors in cattle equipped with virtual fence collars. Boyd et al. [158] applied virtual fencing technology to contain animals and enforce forage utilization with firefighting purposes. Anzai and Sakurai [205] proposed an unmanned robotic vehicle to control grazing cows' distribution. Barbedo et al. [159] carried out a study on livestock real-time detection through UAV images using Deep Learning to assess the reliability to detect cattle with aerial images under suboptimal conditions.

Recently, García García et al. [130] investigated several indicators built from commercial GNSS collar data to describe their potential for the detection of calving on rangelands.

5.3. PLF technologies for buffalo

To date, few PLF technologies have been adapted for buffalo rearing systems. Ermetin [206] used a SWOT analysis identifying key challenges such as the species' temperament, the need for breeder training, and the adaptation of PLF technologies originally developed for dairy cattle to meet the specific requirements of buffalo. However, as suggested by Meo Zilio et al. [207], the implementing new systems for buffalo could encourage wider adoption of PLF technologies, leading to increased production efficiency and animal welfare. Buffaloes are generally more sensitive to stress stimuli than cattle, likely due to their less intensive selection and domestication history. Napolitano et al. [208] investigated the influence of birth weight and time of day on the thermal response of newborn water buffalo calves. They suggested that IRT can detect changes in body temperature associated with hypothermic status. Rodríguez-González et al. [209] evaluated the surface temperature of water buffaloes monitored during transportation suggesting that IRT is a suitable method for accurately assessing thermal changes linked to stress conditions.

In buffalo dairy farms, it is beneficial to predicting the calving time through the behavioral changes related to parturition. Lanzoni et al. [161] investigated the pre-calving behavioral patterns of primiparous Italian Mediterranean buffaloes using video cameras equipped with infrared light, showing that lying, walking, and tail-raising activities are the behavioral changes useful to predict impending calving. Teja et al. [210] also used a digital video recording system to quantify behavioral changes during the final 24 h prior to calving in Murrah buffalo, confirming the same activities as predictors. They highlighted that real-time behavioral monitoring combined with a computerized algorithm using Machine Learning approach could improve the survival, health, and welfare of buffalo cows (dam) and newborn calves.

5.4. PLF technologies for sheep and goat

In recent years, several PLF technologies have been developed and applied to pasture-based system for small ruminants as reviewed by numerous studies [16,79]. Among these, Electronic Identification (EID) systems, including ear-tags, ruminal boluses, and subcutaneous sensors, are the more frequently used and mandatory for sheep and goat farmers according to EU legislation (EC Regulation No. 21/2004). The effectiveness of EID devices has been extensively studied in both sheep [24,40] and goats [36,142]. Ear-tags are the cheapest method but can be lost, used fraudulently, or cause welfare issues if re-tagging is required [40]. Kandemir et al. [211] evaluated the readability of electronic leg and ear-tags in Saanen goats and their effects on animal welfare. Ruminal boluses offer advantages compared to ear-tags due to their inner position, reducing loss and tissue damage. However, sheep require a specific age for safe bolus administration [143]. Garin et al. [212] reported high retention rates of small bolus in 7-week-old lambs. Boluses for goats require higher specific gravity than those for sheep, and current ceramic mini boluses are unsuitable for goats [142]. These authors suggested that leg bands with transponders are a potential alternative but need further investigations for the use in young goats.

Accelerometers, primarily developed for cattle, showed low accuracy and data management challenges in sheep and goat farming [28,79]. However, 3-axial acceleration data loggers have accurately monitored lying behavior in pregnant Saanen × Alpine dairy goats and Saanen crossbred kids [145]. GPS systems could track animal movement and spatial distribution in pasture, as reported by Plaza et al. [147], although concerns on battery lifespan, data transmission, and measurement accuracy [148]. Subcutaneous sensors could provide reliable heart rate and body temperature measurements in sheep, which are useful for detecting diseases and stress [66]. In goats, armpit-injected transponders showed high readability (>98%) but pose challenges during slaughter and may migrate from the original area of injection [142,144]. Among wearable sensors, pressure and acoustic sensors placed on the head of the animal are used to discriminate grazing and ruminating behaviors [151] and estimate feed intake [213].

Virtual Fencing (VF) system has been also evaluated in sheep, replacing physical barriers [154,155]. VF applications face high costs, technological infrastructure requirements, and welfare concerns [214]. Behavioral responses to VF varied individually and with flock size [215,216]. Eftang et al. [217] concluded that goats could learn to avoid electric stimuli but learning curves are influenced by environmental factors. Unmanned aerial vehicles or drones provided feasible solutions for monitoring small ruminants in pasture. They are equipped with cameras, LiDAR, multi-spectral, and other sensors [218,219]. The drones flying above flocks could frighten animals [16], but small and quiet drones at a minimum altitude might not disturb them significantly [220]. Camera-based systems using Machine Learning, like the convolutional neural network, can detect predators and monitor livestock [135]. Among body measurement techniques, Walk-over-Weight platforms and weighting crates offer stress-free alternatives to traditional scales for measuring body weight [163]. These platforms, integrated with EID tags and solar-powered systems, enable automatic weight data collection in pasture-based systems [164]. Infrared thermography measures thermal status non-invasively and is also applied to detect heat stress, estrus, and diseases in cattle, goats, and sheep [165,166]. While many PLF solutions are tailored for extensive sheep and goat farming, their adoption is limited by farm economic stability, trust in new technologies, and openness to innovation among farmers [221].

6. Economic, environmental, and social advantages offered by PLF tools for sustainable pasture-based ruminant systems

PLF technologies allow farmers to optimize resource allocation, providing economic, environmental, and social benefits [222]. Real-time data on animal health, behavior, production performances and pasture conditions enable for precise feed adjustments, reducing waste and improving efficiency, thus reducing operational costs, boosting profitability [223]. Additionally, early detection of health issues reduces veterinary costs and losses from disease outbreaks [17]. PLF optimizes grazing patterns and pasture management, preventing overgrazing, promoting soil health, and reducing its erosion [224]. Moreover, it also facilitates better nutrient management, reducing runoff and the associated risks of water pollution [225]. Precision agriculture farming lowers the environmental impact by applying fertilizers and pesticides only where needed, decreasing the leaching risk and greenhouse gas emissions [226,227]. Furthermore, improved livestock feed efficiency reduces methane emissions per unit of product, contributing to a lower carbon footprint [228]. The adoption of PLF enhances animal welfare through timely and appropriate care, detecting early illness or distress signs [229]. Information and communication technology (ICT) enables the tracking of animal productions, enhancing transparency through the value chain. In rural communities, PLF fosters innovation and creates employment opportunities, particularly in technology management and data analysis. By making farming more efficient and sustainable, PLF helps secure the livelihoods of farmers, ensuring the viability of rural communities and promoting a higher standard of living [230]. Overall, PLF represents a transformative approach to livestock management, aligning economic goals with environmental sustainability and social responsibility [139].

Studies in international literature highlight the potential of PLF tools to mitigate the environmental impact of different intensive livestock systems [231,232].

Regarding grazing systems, PLF tools have the potential to reduce environmental impacts by promoting more sustainable livestock management practices. However, to the best of our knowledge, no scientific studies have directly evaluated the effects of PLF tools on the environmental impact of grazing systems using the Life Cycle Assessment methodology, which is currently one of the most widely employed approaches for evaluating the environmental impacts of agricultural and livestock systems.

The effect of smart farming technologies on extensive livestock farming was mainly evaluated indirectly in terms of environmental sustainability. For example, virtual fencing has been suggested as a tool for enhancing sustainability within the Efficiency, Substitution, and Redesign (ESR) framework. This tool increases resources efficiency, and reduces risks to wildlife, thereby contributing to the sustainable redesign of grazing systems [233].

The use of PLF tools in grazing systems was investigated primarily in the context of greenhouse gas emissions, especially methane. For example, real-time individual data on live weight can facilitate targeted nutritional supplementation for underperforming animals, which helps reduce methane emissions [234]. Improving forage quality by considering the type, quality and maturity of herbage mass in pasture has also been suggested as a strategy for mitigating methane emissions in ruminants [117,235]. Zubieta et al. [235] estimated that optimizing forage quality could lead to a 55% reduction in methane emissions from grazing cattle and sheep. In this context, hyperspectral and multispectral imagery from drones, satellites, and handheld cameras can predict above-ground biomass and crude protein content in real time for grazing paddocks [236]. In semi-arid regions, these technologies assist in estimating forage mass and soil water content, enabling efficient use of soil nutrients and water while preventing long-term resource degradation [237,238].

Moreover, integrating multiple tools, such as topography, environmental temperature, predation risk, and competition for heterogeneous resources, with PLF technologies may support the development of wildlife-friendly strategies that also maximize environmental sustainability. Di Virgilio et al. [133], conducted a study on Merino sheep in Patagonian rangelands, combining data from animal-attached multi--sensor tags with landscape data layers obtained from a Geographical Information System. This approach fits into the concept of “Agriculture 4.0″, which integrates sensors, robotics, the Internet of Things, cloud computing, data analytics, and decision support systems, representing a new era in agriculture production [239]. As highlighted by Hurst and Spiegal [239] well-designed and responsibly implemented PLF technologies can provide benefits for both humans and the environment. However, there is still a significant gap in research addressing the needs, constraints, and impacts of the adoption of PLF in rangelands. It is still unclear whether these rapidly evolving technologies will result in sustainable social and ecological outcomes or whether they are being developed responsibly, with adequate attention to the needs of end users and broader societal implications.

7. Prospects, knowledge gaps and research approaches

The integration of PLF technologies can revolutionize grazing management by providing real-time data and insights [229]. Given the current importance of GHG emissions, PLF tools can contribute to emission reduction by measuring and potentially adjusting feeding, monitoring temperature and other parameters [225]. However, significant knowledge gaps need to be addressed, including the long-term effects of PLF on animal behavior and health, economic viability for small-scale farmers, and optimal integration of various technologies to maximize benefits [36].

By providing real-time data, PLF enables farmers and stakeholders to identify and take timely action on animals raised in suboptimal conditions [35]. Smart technologies can facilitate more informed consumers choices and serve as the basis for innovative business models.

PLF systems generate vast amounts of data that must be securely stored, readily analyzed and user accessible. Therefore, further efforts are required to develop scalable and secure data storage systems, incorporating distributed storage frameworks, optimized data compression algorithms, and integrating long-term archiving solutions. In this context, the future adoption of artificial intelligence tools offers promising prospects for advanced data processing, improved decision-making, and integration of different sensor inputs, thereby enabling more effective livestock monitoring and management.

The exchange of information across the feed-animal-food chain holds great potential for optimizing livestock production [240]. According to Banhazi et al. [35], the availability of cost-effective automated identification systems, concerns about data privacy, and inconsistent supply of traceability products hinder the progress of traceability and PLF integration. Data privacy raises question ownership, property rights and usage. On the other hand, business models could add value by converting spatially explicit big data into actionable information for farmers and regulatory authorities [241]. In addition, ICT will intensify responsibility and accountability challenges associated with new technologies. Accountability for mismanagement or errors with economic and environmental impacts is crucial [222]. High costs and limited knowledge and skills are significant hurdles for technology adoption, particularly in developing countries [242]. Thus, access to the latest technologies may remain restricted only to large and industrialized farms. The digitalization of agriculture might further influence employment opportunities and job profiles in the sector [243]. Another emerging challenge is combining the farmers' knowledge and experiences with new technologies [36]. Research should focus on interdisciplinary studies combining animal science, agronomy, and data analytics to develop comprehensive PLF solutions [244]. Pilot projects and case studies in different grazing environments can provide valuable data, while collaborations with farmers can ensure practical and user-friendly technologies. Some studies suggest that PLF may pose risks to animal welfare through both direct and indirect harm [243]. Addressing these gaps through targeted research will be crucial for fully realizing PLF benefits in ruminant grazing systems.

CRediT authorship contribution statement

Sara Marchegiani: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Giulia Gislon:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Rosaria Marino:** Writing – original draft, Investigation, Data curation. **Mariangela Caroprese:** Writing – review & editing. **Marzia Albenzio:** Writing – review & editing, Visualization, Investigation. **William E Pinchak:** Writing – review & editing, Visualization. **Gordon E Carstens:** Writing – review & editing, Visualization. **Luigi Ledda:** Writing – review & editing, Visualization. **Maria Federica Trombetta:** Writing – original draft, Investigation, Conceptualization. **Anna Sandrucci:** Writing – review & editing, Investigation. **Marina Pasquini:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Paola Antonia Deligios:** Writing – review & editing, Data curation. **Simone Ceccobelli:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, 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.

Ethics Statement

Not applicable: This manuscript does not include human or animal research.

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Data availability

No data was used for the research described in the article.

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